How the presence of FDI impacts upon productivity within UK owned plants in the North East of England's manufacturing sector

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Abstract

The North East voted overwhelmingly to leave the EU in the Brexit Referendum of 2016, despite it being one of the regions of the UK which benefited most from EU funding, and being one of the few regions which had a positive balance of payments with the EU. This thesis looks at how foreign ownership, with a focus on EU ownership, impacts upon productivity in the manufacturing sector in the North East of England.

The North East is a region known for its manufacturing heritage, but as the UK economy has shifted away from manufacturing, moving towards a service base, the region has seen a decline in prosperity and employment. It has become one of the poorest regions in England and to compensate for this, successive Governments have introduced incentives to attract more productive foreign direct investment (FDI) plants to boost regional prosperity. Chapter One compares UK-owned, with foreign-owned plants in terms of productivity in the North East manufacturing sector. It shows that, overall, the impact of foreign ownership is positive but statistically insignificant, suggesting that there is no difference between UK and foreign ownership regarding productivity. However, when ownership type is separated into three groups (EU, US and Rest of the World (ROW), owned), some ownership groups did have a significant impact on productivity. Both US and ROW ownership had a positive and significant impact on productivity, when compared with UK ownership, while EU ownership had a positive but insignificant impact on productivity when compared with UK-owned plants.

Some studies within the literature, such as cross-country studies by Meniago and Lartey (2021), Herzer (2012), and Herzer and Donaubauer (2018), and micro-data studies by Benfratello and Sembenelli (2006), Salis (2008), and Stiebale and Reize (2011), indicate that the average effect of foreign ownership is small but there are heterogeneous effects depending on the nationality of the owner. Informed by these findings, further investigation was undertaken, drilling down into more specific ownership groupings within the clusters, and refining the insignificant impact of broad foreign ownership, into a more detailed and specific understanding of the impact of ownership type in the North East.

Harris and Robinson (2002) found this when comparing the impact of foreign ownership across sectors in the UK manufacturing sector. Görg and Hijzen (2004) found evidence of intra-industry spillovers due to the presence of foreign-owned plants. These spillovers were dependent upon the characteristics of both domestic and foreign-owned plants. While the analysis used in Chapter One shows the ownership effect on productivity, it does not show how the presence of foreign-owned firms in the North East impacts upon productivity in UK-owned plants. This can be done by examining

and comparing productivity in industry groupings. Using industry groupings alone however fails to capture the full picture of plant interlinkage, as such an approach assumes that plants interact only with other plants within the same industry. A solution to this is to use clusters based upon industry linkages, to give a more realistic representation of interlinkage within the supply chain. There is currently no set cluster configuration for the UK manufacturing sector. Therefore, the clustering algorithm developed by Delgado et al (2016) is adapted by this work for the UK manufacturing sector, creating a configuration of 46 clusters.

Using these clusters, the spatial concentration of foreign-owned plants in relation to UK-owned plants is calculated using the Scholl and Brenner (2016) spatial concentration index. This distance-based index overcomes the Modifiable Areal Unit Problem (MAUP) which is common in many spatial concentration indices. The Scholl and Brenner index makes it possible to estimate the way in which an increase in the presence of foreign-owned plants within a cluster impacts upon productivity within the UK-owned plants in the same cluster.

Overall, the results indicates that the increased presence of foreign ownership within the cluster impacts positively on productivity in UK-owned plants, although this impact is statistically insignificant.

Separating ownership into further groupings, it was found that the presence of US- and EU-owned plants has a positive but insignificant impact on productivity, while an increase in ROW-owned plants has a negative, but insignificant impact on productivity in UK-owned plants. As a comparison group, the impact of the presence of UK-owned plants was also estimated. An increase in the presence of UK-owned plants within a cluster had a negative and significant impact on productivity in other UK-owned plants in the same cluster. In the literature, different ownership groups are shown to have different influences across sectors. Positive spillovers have also been found to be related to the characteristics of the host country or region. Research by Goldar and Banga (2020) on FDI origin and Indian manufacturing firms found a positive effect from FDI on Total Factor Productivity (TFP) as well as positive FDI productivity spillovers to domestic firms, with the impact being greater when it originated from developed countries, such as the US and Europe.

Assuming EU-owned plants would, over time, cease to invest in the region and leave as a result of the UK's decision to leave the EU, it could be argued that North East productivity may not be as impacted by Brexit as previously thought. However, this would not take into account the loss of jobs and income that the North East would experience. Focusing solely on EU-owned plants when examining the impact of Brexit fails to consider the motivation of non-EU owned plants investing in the region. These plants may have specifically set up in the North East to access the EU Single Market, or benefit from Freedom of Movement. With an increase in trade barriers resulting from Brexit due to lack of access to the EU Single Market, potential skilled labour shortages through removal of Freedom Of Movement, and removal of access to development funds administered by the EU, many such non-EU owned plants may choose to reduce their presence or leave the region, having a negative impact upon the North East regional economy.

Contents

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1. Introduction

This thesis has been undertaken to promote a deeper understanding of the specific impact, including any spillover benefits of Foreign Direct Investment (FDI) in manufacturing in the North East of England. The North East is an area characterised by long term decline, and associated social deprivation, following the end of the heavy industry boom of the 19th century. Attempts to reverse the continued economic decline since 1960s have mainly centred on Central Government and regional bodies supporting FDI by using subsidies in various forms to attract such investment. The effectiveness of this strategy will be explored through this first full evaluation of existing North East FDI. Currently, there are no studies focused solely on the impact of FDI in the North East, with the region usually being amalgamated in the broader "North of England" category for the purposes of analysis; this is despite the North East having different challenges and assets regarding geology, location, transport infrastructure, ports, labour pool, and research potential.

I have used the timeframe 1984 to 2014 for the research. This period begins after the accession of the UK to the EU in 1972 and covers the period of the announcement (1986) and the launch of the EU Single Market, in 1993, and ends in 2014 so the data is uninfluenced by the announcement of the Brexit Referendum in 2015.

My research objectives are:

1. To establish if there is a productivity advantage in foreign-owned firms over UK-owned firms in the North East of England.
2. To establish a cluster configuration for UK manufacturing which allows identification and comparison across UK regions of manufacturing specialisation.
3. To analyse the impact of the presence of foreign-owned firms on productivity in UK-owned firms in the same cluster by region.

This thesis contributes to new learning in its focus on the North East region specifically, and the interaction between FDI and industry classification, looking at the impact on productivity advantage. I develop the first, unique cluster configuration for the UK manufacturing sector, based on Delgado's clustering algorithm, which enables consistent analysis of spillovers across regions, and accurate comparisons between regions. Using this, I compare the North East region, with the North of England and the South East regions and establish that the industrial investment requirements of the North East are quite specific, differing from the wider North of England region, in which it is usually included for analysis purposes. The industry types concentrated in the North East are very different from those in the South East and furthermore FDI in the South East is seen to have the opposite (negative) impact on UK-owned plants in the same cluster, whereas the effect of this investment is broadly positive, both in terms of increased productivity in through direct ownership effects and through positive spillovers.

The UK has been one of the world's most successful countries in attracting FDI and currently ranks second in Europe in attracting FDI, accounting for 17.3% of Europe's inward investment (Arnold et al., 2024). Th UK is most successful at attracting FDI in areas where it has a comparative advantage, such as digital, financial, and business services (Arnold et al., 2024). Until 2020, the UK had access to the European Union (EU) Single Market and was not restricted by the "rules of origin" relating to inputs, enjoyed tariff-free trade, and freedom of movement of goods and services. This, alongside low shipment costs of physical goods, a protective legal environment and access to skilled labour made the UK a very desirable place for FDI (Dhingra et al, 2017).

In 2019, the largest proportion of international investment in the UK came from the EU (43.7%), followed by the USA (24.5%) (ONS, 2020). Most was invested in Financial Services (27.79%), followed by Professional, Scientific and Technical Services (10.52%). Most of the investment from the EU was in Financial Services (7.76%), followed by Other Services (5.77%), and then Retail and Wholesale (3.77%). FDI has been encouraged in the UK over this time frame and is an important aspect of the UK's economic performance (Dhingra et al, 2017). However, with the UK's decision to leave the EU in 2016, there was perceived to be a risk that the level of investment would fall. Japan, after the referendum, issued several warnings to the UK government, stating that without a "soft" Brexit there was a high risk of Japanese and other FDI leaving the UK. The Japanese ambassador, Koji Tsuruoka, cautioned the UK government in 2018 by stating "If there is no profitability of continuing operations in the UK — not Japanese only — no private company can continue operation.", according to Hodgson, (2018).

FDI has long been perceived to have positive benefits on the recipient areas and businesses, due to the advantageous characteristics of foreign-owned firms, which allow them to compete successfully with established domestically-owned plants (Hymer 1976). Such advantageous characteristics include increased capital, advanced technology, and improved managerial and technical skills, which may hopefully be transferred to local firms, which would then see a consequent improvement in their productivity and growth.

Some theories suggest that the effect of FDI within the host country is dependent upon the motivation behind the investment. Driffield and Love (2007) and Dunning (1988) state in their theories that the positive or negative impact within the host country from FDI is dependent on FDI motivation. Foreign-owned plants have the potential to crowd out domestic plants due to their advantageous technology and knowledge outlined above. (Dunning 1988). They may also try to limit access for domestic plants to these characteristics, meaning domestic plants are unable to assimilate their knowledge and technology and benefit from them. Additionally, as highlighted by Driffield and Love (2007), foreign-owned enterprises can choose to set up plants in low-cost regions and compete on efficiency savings rather than through bringing in more technologically advanced practices which may then be shared in the host area. The findings on the impact of FDI on host countries' productivity in the literature is mixed, many suggesting it is dependent on the host countries' absorption capabilities (such as Hayakawa, Lee and Park (2013), and Konings (2001)) as well as the FDI origin (such as Doms and Jensen (1998), and Aitken and Harrison (1999)), and motivation (such as Guadalupe, Thomas, and Kuzmina (2012), and Schiffbauer et al. (2017)).

The literature indicates that the effect of FDI on a cross-country level and a micro level is also mixed. Studies such as those by Driffield and Love (2007), and Dunning (1988), find that the benefits from FDI are not always positive, as originally suggested by Hymer, in his theory of 1976. Benefits can be more dependent upon the host country's ability to assimilate the proposed advantageous characteristics of FDI i.e. the potential introduction of and access for the host country to more advanced technology, improved managerial and production techniques, and the introduction of capital.

On a cross-country level, Cipollina, Giovannetti, Pietrovito, and Pozzolo (2012) found that FDI had a positive impact on growth across 14 manufacturing sectors in both developed and developing countries. Amann and Virmani (2014) also found that the impact of FDI was positive on TFP in emerging countries, and the impact was greater when more Research and Development (R&D) intensive countries invested. Al Nasser (2010) also found that host characteristics impacted upon the influence FDI can have within a host region. Herzer (2012) and Herzer and Donaubauer (2018) found the same, although they also found the overall impact of FDI was negative, differing from previous studies.

On a micro level, several studies found that host characteristics, such as educational attainment, historical factors, market size or wage rates, were important factors in terms of the impact FDI. Konings (2001) who examined FDI across three Central European countries (Poland, Bulgaria, and Romania) found FDI had a positive impact in only one of the countries. Poland. Hayakawa, Lee and Park (2013) found host country wages can have both a positive and negative impact on the level of FDI in within three Asian countries: Japan, Korea, and Taiwan. There was a negative relationship between wage increases and inward FDI, but a positive impact between outward FDI and wage level. The length of time which has elapsed since the investment was made also plays a role in the impact of FDI. In the short term, FDI can have a negative impact upon domestic plants, but in the mid to long term can boost growth and productivity within these domestic plants (Adams (2009), using sub-Saharan countries and Dinh, Vo, The Vo, and Nguyen (2019) within developing countries).

There are studies which found that FDI had no impact on productivity, and that the advantage perceived stems from the acquisitions of more productive domestic firms. Guadalupe, Thomas, and Kuzmina (2012) in Spain, and Arnold and Javorcik (2009) in Indonesia, found evidence that the already productive domestic plants were more likely to be acquired by foreign-owned firms. However, after acquisition, these cherry-picked acquired firms still performed better than would have been the case should the acquisition not have taken place. Others, such as Benfratello and Sembenelli (2006), using Italian data, and Salis (2008) in Slovenia, have found that foreign ownership has no impact.

The North East of England has traditionally been able to attract FDI projects to the region through government incentives and grants (Jones and Wren, 2008), examples being Nissan in Sunderland in 1984, and Siemens in North Tyneside in 1997. Jones and Wren (2008) examined the Relative Regional Performance in terms of a region's FDI investment projects relative to the share of UK employment between 1985 and 2005. The North East was the best performing English region in FDI projects relative to employment share.

However, while the North East attracts FDI and it creates jobs, there is no evidence regarding how the presence of FDI impacts directly on productivity, either through increasing productivity in FDI recipients, or through the presence of FDI impacting on UK-owned plants productivity. This work examines the estimated effect of foreign ownership of plants in the North East of England, over time, in comparison to UK-owned plants, something the previous studies discussed above have not covered.

The North East of England is a region where there has been very little specific research focus. In recent years there has been an increased focus on improving the North generally, starting during the Coalition Government 2010-2015, through to the Boris Johnson Conservative Government's 'Levelling Up' agenda and the Government White Paper published in February 2022. However, studies tend to group the North East of England in with the collective "North", which stretches from Liverpool and Manchester in the West, to Hull in the East and up to the Scottish borders (PricewaterhouseCoopers, 2021). This fails to capture the differences in the local economies in the North of England, as well as diminishing the difficulties related to regional connectivity, especially in terms of transport links (Giovannini & Raikes, 2021). As the North East attracts a large amount of FDI in comparison to other regions in England, examining the impact such foreign-owned plants have on domestically-owned plants in the surrounding region is necessary and beneficial. As Driffield and Love (2007) and Dunning

(1977, 1988) highlighted in their models on FDI, the motivations for FDI may not always result in beneficial spillovers to the surrounding firms or host region. This thesis examines how the presence of FDI in the North East of England impacts upon the productivity within plants in the manufacturing sector. While there have been studies that have looked at foreign ownership and productivity by region in the UK, none have focused solely on the North East.

As the literature would suggest foreign-owned plants are expected to be more productive than domestically-owned plants (in Chapter 3.1), this thesis first compares how foreign-owned plants compare in reality with domestically-owned plants in terms of productivity. This will be done in two stages; the first stage will be to group all foreign ownership groups together and calculate whether there is an ownership effect in terms of productivity compared to domestically-owned plants. The literature (in Chapter 3.2) identifies that origin of FDI can also impact upon productivity, so the second stage will be to separate ownership into three groups: EU-owned, US-owned, and Rest of the World (ROW)-owned. The individual ownership effects can then be calculated in comparison to domestically-owned plants.

While the comparison between foreign-owned and domestically-owned plants is useful, it does not show the impact of FDI via spillovers on domestically-owned firms. The literature (in Chapter 3.3) shows that the presence of foreign-owned plants can result in spillovers, sometimes beneficial, but not always so, between the foreign-owned plants and the domestic ones. These include positive impacts such as the introduction of more advanced technology, benefiting from a more highly skilled labour pool, and an increased research base, and negative impacts such as the crowding out of domestically-owned firms, prevention of the advantageous characteristics being assimilated into the domestically-owned plants and the competition effect, with the exploitation of low-cost labour.

To examine the impact of the presence of foreign-owned plants, the spatial concentration of these plants will be calculated using Brenner and Scholl (2016) spatial concentration index. This could be done within industry groups, such as three-digit or two-digit Standard Industry Classification (SIC). However, this method fails to capture the full linkages between plants that may be associated with plants from other SIC classifications. A solution to this is to use clusters of industries; groups of industries which are characterised as networks of production of strongly interdependent firms linked through value added production chains (Roelandt & Den Hertog, 1999). The use of industry clusters allows the researcher to analyse the relationship between industries within regions and provides a better understanding of how industries are interlinked within a region. Cluster analysis has advantages over the more traditional sectoral analysis as it can take into account the horizontal and vertical linkages, knowledge flows, and interdependencies (Rouvinen & Ylä-Anttila, 1999).

For the UK, there is no comparable cluster configuration available. Clusters are usually calculated per area or based upon policy makers' objectives; this makes it very difficult to compare clusters between studies as they are not based upon the same data. To overcome this, the Delgado (2016) clustering algorithm will be used. The main advantage of using this algorithm is that it creates a comparable cluster configuration across the whole of manufacturing industry, making it possible to create a standardised configuration that can be applied across regions or states, allowing for meaningful comparisons. The work was initially done using the US North American Industry Classification System (NAICS) classification, but it has been adapted for UK manufacturing data, creating a configuration of clusters for the entire of the UK. The algorithm calculated 46 clusters of industries for the UK manufacturing sector. The spatial concentration of foreign firms will be calculated within these clusters. Foreign ownership will be separated into the three ownership types: EU, US, and ROW to estimate the impact the different ownership types will have.

While this thesis focuses on the North East of England, it is also beneficial to compare the results from this region with other regions in the UK. The South East of England is the region that is the closest to the productivity frontier. It is more likely to attract high value-added investment and has regional characteristics which would result in higher productivity such as better transport links, higher wages, and a greater level of R&D[1]. There is value in comparing how foreign-owned firms perform relative to domestically-owned firms in the South East and the North East. Foreign-owned plants may have chosen to establish low value-added plants in regions like the North East, exploiting the lower labour and rent costs. This may result in these foreign-owned plants adding very little to regional productivity in the North East.

This thesis uses plant level micro data for the UK manufacturing industry between 1984 and 2014. This range of dates captures the announcement of the single market in 1986, its introduction in 1993, and terminates in 2014 at the last available clean data prior to the Brexit referendum debate and legislation in 2015. The data is from the Annual Respondents Database and the Annual Business Survey collected by the Office of National Statistics. The focus is on the manufacturing sector, as data for the

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[1] The South East could be classified as a core region, and the North East a periphery region from the model presented by Krugman (1991). Core regions having increasing returns, attract workers due to higher wages, there is a higher concentration of producers and production, and receive more investment from both the private and public sector (Danson 2003). Whereas periphery regions, which tend to be more reliant of old traditional industries, see outward migration of workers (mainly skilled workers) from the region, and a fall in the level of investment. This results in an increase in unemployment, a fall in regional output and a fall in regional productivity.

services sector was not included in these data sets until 1997, after the introduction of the EU single market.

My findings indicate that overall, the direct effect of foreign ownership in the North East is positive, suggesting foreign-owned plants have a productivity advantage over domestically-owned plants, however the coefficient is insignificant. When separating the foreign ownership into EU-, US- and ROW-ownership, both US- and ROW-owned plants have a significant productivity advantage while the EU ownership's productivity advantage remains insignificant.

When examining how the presence of foreign-owned plants impacts upon domestic plants within clusters generated using the Delgado et al (2016) clustering algorithm, an increase in the presence of foreign-owned plants within a cluster has a positive, but insignificant, impact upon productivity within the domestic plants in the same cluster. Examining the different ownership types, an increase in the presence of EU- and US-owned plants has a positive, but insignificant influence on productivity in UK-owned plants in the same cluster. The impact of an increase in the presence of ROW plants is negative but again insignificant. As a comparison group, the impact of an increase in the presence of other UK-owned plants is also estimated. In every case, an increase in the presence of UK-owned plants in the same cluster has a negative and significant impact on productivity within other UK-owned plants in the same cluster.

The remainder of the thesis is laid out as follows: Chapter 2 presents the evolution of the North East industrial base with descriptive statistics of the North East manufacturing sector between 1984 to 2014, Chapter 3 examines the literature surrounding foreign ownership, spatial spillovers and productivity, Chapter 4 reviews the data that will be used for this analysis, Chapter 5 examines how foreign ownership impacts on productivity within plants in the North East of England, Chapter 6 presents the clustering algorithm and the cluster configuration for the UK manufacturing industry and Chapter 7 presents an analysis of how the spatial concentration of foreign-owned plants impacts upon productivity in UK-owned plants in the North East of England, with Chapter 8 concluding the thesis.

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2. Historical Overview of the North East Manufacturing Industry

2.1 Introduction

The North East of England's regional economic growth has historically come from the so-called heavy industries. Its natural resources, deposits of coal, minerals and iron ore, resulted in the growth of these heavy industries including mining, especially of coal, leading to coke production, iron and steel manufacture, development of rail transport and locomotive production, shipbuilding, engineering and armament manufacture (Hudson, 2005).

In the nineteenth century North East regional growth was powered by strong intra-regional interdependencies, dominated by linkages between a few large conglomerates in coal mining, iron and steel, shipbuilding, armaments and engineering, with emerging chemical industries (Clark, 2005). Companies and conglomerates mining for raw materials supplied iron and steel production which in turn supplied the shipbuilding industries which emerged, centred on the wide deep river mouths of the Tyne and Wear, and armament production. Engineering businesses then developed to support the requirements of the mining, steel and other heavy industries. International markets, often protected by the British Empire, were established, and new markets ensured in growing areas where British based capital held a dominant position, such as South America (Hudson, 2005). Markets here and within the UK expanded with global industrialisation. A strong driver was the embracing and driving forward of technological advances.

Innovations within the region included George Stephenson following James Watt of Greenock, in improving the efficiency of steam powered engines and translating these into transport locomotives to haul goods within a region with deep existing river systems between urban centres and the sea. Rudimentary mineral locomotives advanced to produce the steam railway in 1825. Coal was thus moved by rail to navigable rivers and then through docks such as those at Hartlepool and Seaham Harbour as well as the major ports at Sunderland and Newcastle upon Tyne, to supply London and other markets. Development of the railways, and the iron and steel industry on Teesside led to investment in straightening and deepening the Tees, so developing a large seaport at Teesmouth complementing those at Sunderland and Tynemouth, making it possible to export steel and other goods across the globe.

Although the North East was able to grow rapidly during the Industrial Revolution and became one of the most affluent regions in the UK (Kitson & Michie, 2014), it can be argued that this wealth was unevenly distributed, highly benefitting the few business owners, while many thousands of people worked in dangerous conditions, with few legal protections. The availability of this work however was relatively stable. Hundreds of thousands of men were employed in the manufacturing sector or its supply chain[2] throughout the region, up until the First World War. The seeds of subsequent decline in the Teesside steel industry however can be seen in poor decision making over this period. Steel makers Bolkow Vaughan failed to invest in new technology in the 1890s and failed to diversify into more profitable areas of steel production such as pipes. They failed to invest in their own supply chain of coal mines and became over reliant on failed promises of finance from the UK Government during World War 1 leading to reliance on costly bank loans by 1918 (Abé, 1996). However, the Teesside chemical industry was boosted in 1914 through investment by the Ministry of Munitions and the creation of ICI in 1926.

Following World War One due to the drop in global demand from the Great Depression, and the widespread protectionism of the 1930s, unemployment in the North East rose as large factories and businesses either laid off workers or closed (Kitson & Michie, 2014). Regional decline in North East manufacturing was underpinned by the collapse of construction and industrial expansion in the international markets formerly supplied by the region, through the worldwide financial depression in these decades.

The 1930s and World War Two prompted re-armament, and an increase in demand for products of these heavy industries which lasted for the length of the war and into the immediate post war period.

Post Second World War, new industries expanded in the North East, such as chemicals and plastics. These employed some of the skilled unemployed labour that was available following the drop in demand in traditional industries. However, UK manufacturing continued to find it difficult to compete internationally because of the increased availability of cheaper steel and other products from abroad, with manufacturers moving production to lower cost regions. US loans and Marshall Plan aid to Britain was not invested into modernising industrial capacity, showing lack of vision by the then Labour and subsequent Conservative Governments. These failed to recognise the importance of industrial and infrastructure reconstruction, Britain's financial near bankruptcy, and the UK's declining role on the international stage. The Marshall Plan finance was used to maintain gold and dollar reserves, and on defence spending, in an ultimately futile attempt to retain Britain's place as banker for the so-called Sterling Area, the UK's former powerful place in the world and to maintain imports for post war reconstruction, including food and timber. Germany (also Japan and France), in contrast, bid for

[2] In 1919, at the peak of the coal mining industry, there were 200,000 men employed in the coal mining industry, which was roughly 10% of the entire population of the North East at the time Kitson, M., & Michie, J. (2014). *The deindustrial revolution: the rise and fall of UK manufacturing, 1870-2010*. Centre for Business Research, University of Cambridge. .

Marshall Aid and other US support based on a strategic four-year plan to reconstruct industry and infrastructure. UK loans were finally repaid to the US in 2006.

In the 1960s and 1970s UK Governments attempted to attract new private sector investments to strengthen the regional economy. However, these investments resulted in industries which could be said to have been "global outposts sat at the limits of global chains of command and although offering diversification provided low value added, low skill activities" (Austrin & Beynon, 1979).

During the 1970s a combination of factors, such as the oil crises in the Middle East[3], and government policy[4] resulted in the overvaluation of the UK exchange rate (Kitson & Michie, 2014) and a fall in demand both at home and abroad for products produced in the North East and so the continued decline in manufacturing jobs.

Major structural changes in the region's industries included steel companies closing or merging, eventually becoming British Steel, resulting in the closure of numerous smaller plants across the region and large numbers of skilled workers being made unemployed. In the coal mining industry, demand switched from coal to oil and gas, and the importing of cheaper coal. This caused the migration of workers away from the traditional mining areas into the nearby cities or away from the region all together. The decline in the manufacturing industries resulted in a decline in demand for transport, mainly rail transport. Because of these closures, the vast railway network that connected the region's manufacturing plants started to close[5], adding to the level of unemployment in the region, not only through the closure of railway depots and stations but also preventing workers from travelling to employment.

This decline in employment and plants within manufacturing was not limited to the North East of England. The economy as a whole was transitioning to more service-based industries. The manufacturing sector was seen as old and unnecessary, and those regions that were dependent upon

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[3] In 1978, the Iranian Revolution resulted in a decrease of output by Iran which caused global panic and caused oil prices to rise. Then in 1980, following the Iran-Iraq War, Iran almost stopped production and Iraq heavily reduced their output, causing prices to rise again

[4] The decision by the government to focus on reducing high inflation resulted in the reduction of the state's role in the economy through the privatisation of the nationalised manufacturing industries of shipbuilding and steel and iron works, deregulation of financial markets, removal of trade unions, reduction in public expenditure, and the promotion of free market forces.

[5] In 1962, Richard Beeching was assigned, by the Ministry of Transport, to cut losses in the railway industry. His proposal included closing over 5000 miles of railway that had very little traffic, along with the closure of stations. His findings can be found in "The Reshaping of British Railways Part 1: Report" (1963).

it for jobs and prosperity were left with little investment and increasing unemployment, resulting in the deepening of regional inequality (Kitson and Mitchie, 2014).

During the 1980s the decision by the then Conservative Government to focus on reducing high inflation through the reduction of the state's role in the economy, the privatisation of the nationalised manufacturing industries of shipbuilding and steel, deregulation of financial markets, removal of trades unions rights, reduction in public expenditure, and the promotion of free market forces had profound implications for the region. Cutbacks were made in central Government funding of regional policy. Privatisation of uneconomic nationalised industries, and subsequent rationalisations within these took place. Previously nationalised industries had co-operated with each other, supporting one another in creating markets for each other's goods. For example, electricity supply and steel industries had combined to create a market for coal which ended on privatisation, leading to the closure of all of the collieries in the North East (Hudson et al., 1991).

Subsequent decline in the large-scale chemical industry was symbolised by the de-merger of ICI in the 1990s, following pressure from financiers within the City of London (Owen & Harrison, 1995) with the less valuable bulk chemical industries being largely sited on Teesside and being sold, scaled back or closed. Some FDI proved highly successful, such as Nissan investing in Sunderland in 1984, some less so, such as Siemens' expansion into North Tyneside in 1997. The North East has therefore found itself having to forge a new industrial path in the twenty first century and this would benefit from region specific research to more fully understand the most effective way in which to achieve this.

Box 2.1 Timeline for the Development and Subsequent Decline of North East Manufacturing Sector

Natural resources were exploited, coal and iron ore were recovered from North East beaches, charcoal produced and surface coal outcrops exploited to facilitate iron smelting. Lead was mined in Weardale, and lime (limestone) burnt for use in building, particularly monastic buildings and cathedrals.

1200s Building wooden vessels for king's fleet recorded.

1300s Coal is obtained by accessing surface outcrops through bell pits, close to navigable rivers, which then served to move the coal to ports, for export abroad, and to London. 15,000 tons in 1377.

1550 Coal fields had been largely owned by the Church, which restricted supply, but following the Dissolution of the Monasteries production expanded. Coal production exported through the Tyne was 15,000 tons in 1377, and remained constant until the Dissolution, but by 1565 was 35,000 tons.

1620s Horse drawn tramways begin to be constructed to move coal from mining sites to navigable rivers, enabling drift mining, and deeper shaft mining of reserves located further from rivers, leading to an estimated increase in coal exports through the Tyne from 35,000 tons in 1565 to 400,000 tons in 1630.

1691, 1692 larger 'iron manufacturies' opened near Sunderland, and iron smelting and nail making for the Sunderland shipyards operating in Derwentside using imported Swedish wrought iron.

1712 Invention of the Newcomen steam engine and its introduction in the region improved pumping of flood water from deeper mines. Shaft depths increased from up to 300 ft in 1700, to 600 ft in 1750, and 1000 ft by 1800, following improvements to the steam pump mechanism.

1730 Earliest crucible steel making furnace in the country opened in Derwentside, Co Durham.

1779 James Watt patents his improvements to the steam engine, increasing the efficiency of power output.

1797 Large iron works open at Lemington on Tyneside.

1812 steam traction engines and locomotives being used for coal transport at collieries in the North East, initially using the wooden rail network but transitioning to iron rails.

1815 George Stephenson improves locomotive steam power efficiency, and constructs his first steam locomotive "Blucher" for moving coal at Killingworth Colliery,

1825 Stockton and Darlington railway – world's first public and freight railway - opened in 1825. George Stephenson appointed engineer in 1821.

1830/40s – rapid expansion of the passenger and freight rail network across the region.

1833 Clarence Railway opens, competitor to the Stockton and Darlington, taking coal and limestone from County Durham to the Tees ports more cheaply, facilitating the development of large docks opened in 1842 on Teesside, and improvements to navigation on the Tees.

1820s to 1840s improved power output from innovations in steam engine design enables deeper mining for coal, through steam powered cages enabling access to deep seams via deep shafts, and powerful pumps to remove flood water.

1841 Consett ironworks opens on Derwentside, after iron ore discovered nearby in 1837. It later shifts to use Cleveland ironstone which is of a higher quality.

1845 George Hudson "the railway king" becomes MP for Sunderland and finances much of the North East's railway infrastructure expansion. Timothy Hackworth establishes a locomotive works at Shildon.

1847 Armstrong's armament factory "The Great Elswick Works" established on Tyneside.

1850 outcrop of ironstone identified and exploited in the Eston Hills, Cleveland. Combined with limestone and coal from County Durham and the proximity of docks and transport infrastructure at Tees mouth, this initiated the Bolkow Vaughan company to build the first blast furnace of the iron and steel industry on Teesside. This was developed from puddling furnaces and iron rolling mills already in existence which had used Scottish pig iron. It supplies the piping for London's sewage redevelopment 1850s and 1860s.

1850 Hudson Dock opens, and shipbuilding is well established at Sunderland, with the first iron ship built there coming in 1852. The last wooden ship is built in 1876. Smith's dock shipbuilding opens on Tyneside and an engine works established at Jarrow.

1859 Large salt deposits discovered on Teesside while boring for water to supply Middlesbrough, preparing the way for the chemical industry on Teesside, moving from Tyneside. The LeBlanc process using salt (NaCl) to produce soda ash used in the chemical bleaching of cloth was established on Teesside from 1806. It was initially hampered by the tax on salt which was removed in 1825 (Rowe, 1998).

1861 – 700 acres of land covered by blast furnaces in Middlesbrough.

1865 Approximately a third of all sheet glass in England is supplied by James Hartley's Sunderland works

1869 Cargo Fleet Chemicals establishes an alkali factory at Cargo Fleet on Teesside.

1874 Middlesbrough has the highest output of iron and steel of all towns in the UK, with one third of the UK production originating here. Research on the vast amounts of slag produced enables it to be made into "scoria brick", used for road surfacing, locally and exported, creating a new income stream.

1875 Gilchrist steel production process introduced on Teesside. Dorman Long established, with technological innovations driving quality, and higher, more cost-effective production.

1890 Open Hearth steel making method introduced and supplants the original Bessemer process as it enables close monitoring of components and enables the use of scrap iron. Produces higher quality alloys and is cost effective.

1912 Miners strike for minimum wage – Government intervenes and extends minimum wage provision to the mines and other heavy industries.

1914 Synthetic ammonia factory built by the government Ministry of Munitions at Billingham on Teesside for use in explosives during World War 1, boosting the chemical industry on Teesside. It required water, air and methane as raw materials, and excellent transport infrastructure (Rowe, 1998).

1919, at the peak of the coal mining industry, there were 200,000 men employed in the coal mining industry, which was roughly 10% of the entire population of the North East at the time.

1927 ICI chemical company formed on Teesside, through amalgamation of smaller firms.

1929 Cost pressures force Bolkow Vaughan into a takeover by Dorman Long, themselves also struggling financially.

1935 Coal Hydrogenation Petrol Plant opened at Billingham on Teesside to produce oil from coal.

1937 to 1945 Rearmament begins, and the war time economy restores demand for the goods and raw materials produced in North East England. Rapid development of ICI Industries at Billingham producing the PIAT anti-tank gun, Resin X (Perspex) for windscreens, fog dispersal techniques on airfields and contributing to the atomic bomb development.

1945 ICI Wilton established producing nylon, polyester, and developing products for fabrics, domestic goods, detergents and antifreeze.

Nationalisation of industries, arguably (Hudson) on terms favourable to the private sector:

- o 1947 Coal mining
- o Steel 1967
- o Ship building 1977

North East industries continued decline due to new centres of production for coal, steel and shipbuilding, and new technologies leading to replacements for coal as an energy source such as oil, and of steel as a fabrication material by carbon and plastic products.

1960 to 1970 Substantial (100) colliery closures across the North East coal field, as reserves are worked out or become uneconomic, retaining only the most economic pits going forward.

1962, Richard Beeching was assigned, by the Ministry of Transport, to cut losses in the railway industry. His proposal included closing over 5000 miles of railway that had very little traffic, along with the closure of stations. His findings can be found in “The Reshaping of British Railways Part 1: Report” (1963)

1960s and 1970s ICI expands to Seal Sands, Cleaner working practices introduced.

1972 Miners Strike for increased wages, picketing of power stations, before negotiating large wage increase and return to work.

1973 United Kingdom joins the EU – then the EEC (European Economic Community)

1974 Oil price rises follow the Yom Kippur War

1974 Miners Strike again for 7% pay rise, and the situation led Edward Heath, the Prime Minister, to declare a state of emergency and introduce a three-day working week. The General Election and the Industrial Relations Act meant that picketing and campaigning were low key compared with the 1972 strike. Edward Heath called a General Election for the 28th of February believing that the country would be in sympathy with him, but the Conservatives were defeated. The Labour Government and the miners reached a deal shortly afterwards and the strike ended.

Governments and the country become acutely aware of the importance of coal to the British economy.

1978, the Iranian Revolution resulted in a decrease of output by Iran which caused global panic and caused oil prices to rise.

1976 First North Sea Oil comes ashore having been discovered in 1966. Production facilities centred in Aberdeen and Norther Scotland.

1960s, 1970s and 1980s British industry was recognised as outdated and rationalisations and reconfiguring of major firms, such as GEC, was supported by Labour and Conservative Governments. This led to large sums being generated but again these sums were not invested in further innovations, on industrial capacity.

1980, following the Iran-Iraq War, Iran almost stopped oil production and Iraq heavily reduced their output, causing oil prices to rise.

1980 North Sea oil revenues, as with Marshall Aid previously, were used to pursue the political aims of the then (Conservative) Government rather than to invest in the country's infrastructure and industry.

1980s ICI expands into Bio products and non-animal protein foods, Quorn.

1984 Nissan opens its vehicle manufacturing plant near Sunderland. The decision by Nissan to locate here was based on the availability of Government incentives, and at least in part because of access to EU markets, although this latter was not publicised by the then Government.

1984 to 1985 Miners strike in opposition to colliery closures, returning to work unsuccessful, and precipitating the end of the coal mining industry.

1986 and 1990 Privatisation of the British Energy Market led to deregulation, and diversification of fuel supply from the staple of coal in the Electricity generating businesses, reducing the market for coal as a fuel for political, financial and environmental reasons.

1987 (October) Black Monday stock exchange crash resulting from interest rate policy issues. All markets except the British market recover by December 1987. Britian was further impacted because of the Hurricane on the day previously impacting on traders attending.

1988 British Steel Corporation becomes British Steel and is privatised.

1988 Shipbuilding ceases on Sunderland despite modern state of the art facilities, through an arrangement with the EU to reduce European shipbuilding capacity. In reality shipbuilding had probably long ceased to be economically viable in much of Europe, production largely shifting to South East Asia.

1992 Black Wednesday – Sterling crisis forces the pound from the ERM, and the Bank of England to invest, and lose, £3bn in a failed attempt to retain the pound pegged to the deutschmark.

1993 Launch of the EU Single Market

1993 Last deep coal mine in Durham closes

1997 ICI broken up into Zeneca pharmaceuticals, located out of the North East region, and the remaining less attractive bulk chemical businesses located on Teesside, which were sold off to foreign-owned firms, leading in 2008 to the last finally being sold to AksoNobel, and largely the end of the large-scale chemical industry on Teesside. This reflected the varying profitability of the diverse businesses and pressure for rationalisation from City investors.

1997 Siemens opened a microchip manufacturing plant in Tyneside, Newcastle
1998 Siemens closed the manufacturing plant in Tyneside, Newcastle, repaying government subsidies.
2005 Last deep coal mine in the region closes, Ellington in Northumberland.
2016 Brexit referendum where the UK voted to leave the European Union

2.2 Overview of National Manufacturing Sector in the Great Britain

The British economy as a whole had been transitioning to service-based sectors since the 1980s, following the economic difficulties and industrial unrest of the 1970s. This transition was prompted by structural issues, including underinvestment in manufacturing and then a shift in policy to a "knowledge" based economy with a focus on services, and the 'City' (Kitson and Mitchie, 2014). One study by Kitson and Mitchie suggested that following the election of the Labour Government in the 1997 General Election, further policies were introduced that favoured the service sector, especially banking, in the UK, arguments being made that these sectors were vital for the future of UK growth (Kitson and Mitchie, 2014).

Figure 2-1 shows the overall picture of the decline in the number of plants in the British manufacturing sector leading up to and including the period 1997 to 2014.

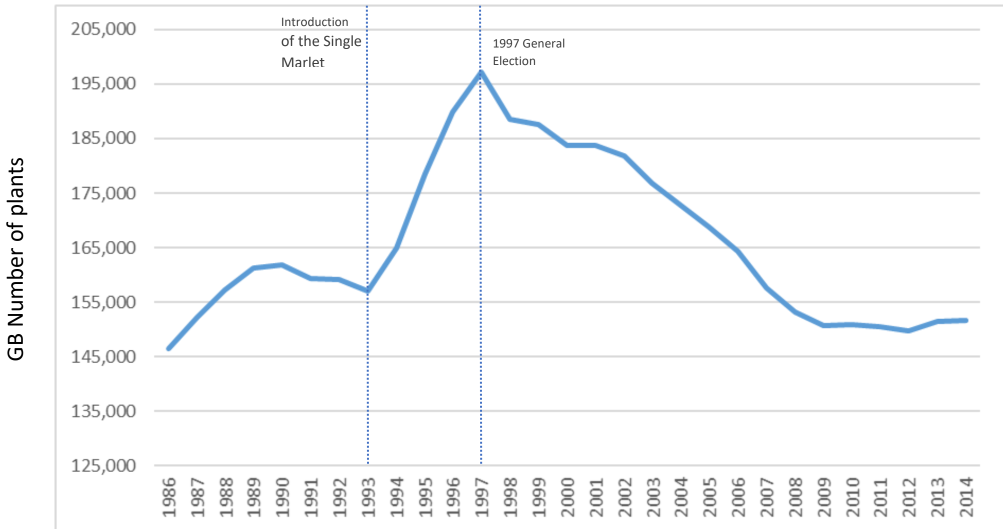

Figure 2-1 Three-year average of the number of plants in the GB manufacturing sector between 1986 and 2014

Source: Annual Respondents Database (ARD Database)

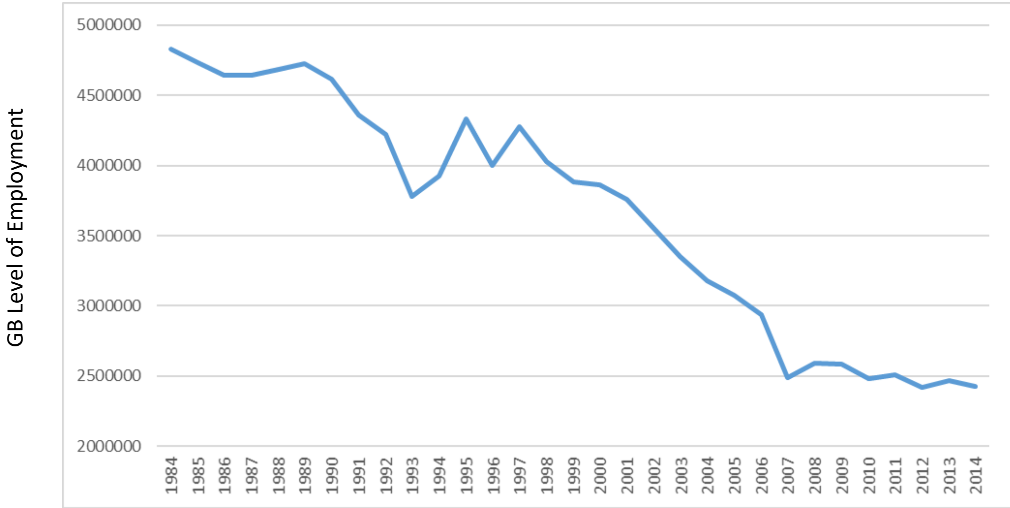

Figure 2-2 The total level of employment in the GB manufacturing sector between 1986 and 2014

Source: ARD Database

Figure 2-2 shows the total level of employment in plants in the Great Britain (GB) manufacturing sector between 1984 and 2014. Employment levels demonstrate the steady decline in the GB manufacturing sector more clearly than simply the decline in the number of plants.

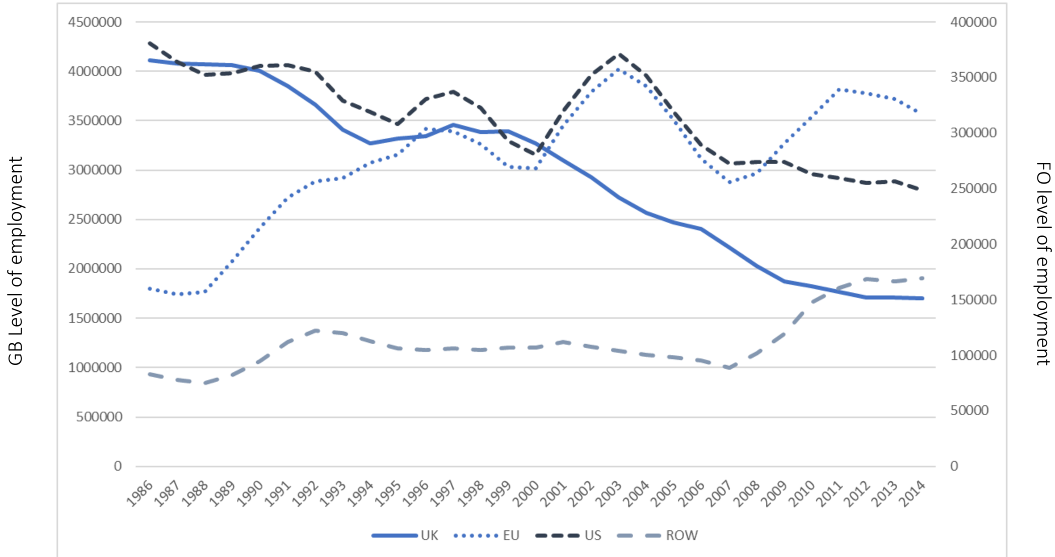

Figure 2-3 The total level of employment in the GB manufacturing sector by ownership group between 1986 and 2014

Source: ARD Database

Figure 2-3 which uses a three-year average, shows the breakdown of employment by ownership group. A three-year average was used to clarify the trends in the data, trends which although present, are less evident from the fluctuating actual numbers. Although the UK-owned plants show a steady decline in employment over the time, they none the less maintain a higher rate of employment, than foreign-owned firms. This decline in employment reflects the increased use of technology superseding some job roles, and the move towards services from large, inefficient heavy industries employing high numbers of workers over the period.

The total employment in US-owned plants also shows a decline, matching the UK-owned declining trend. However total employment in EU-owned and ROW-owned plants contradicted this trend, and increased over the period, potentially reflecting increased investment from these sources following the UK joining the EU and the announcement of the single market. Both EU and ROW ownership groups saw an increase in employment after 1986 and then again in 2008 recovering from the dip caused by the financial crash. Employment in EU and US plants experienced a spike between 2000 and 2007, ending with the financial crash of 2008, before EU ownership recovers in a way not seen in particular in UK-owned plants, but also in US ownership.

By the end of this trend period, employment in EU- and ROW-owned plants is greater than it was at the beginning of the period, while the US and UK employment is lower compared with the start of the period. Data from this time frame has been selected because, although it appears dated, it is uncorrupted by any discussion of Brexit, the relevant legislation having been brought forward in 2015.

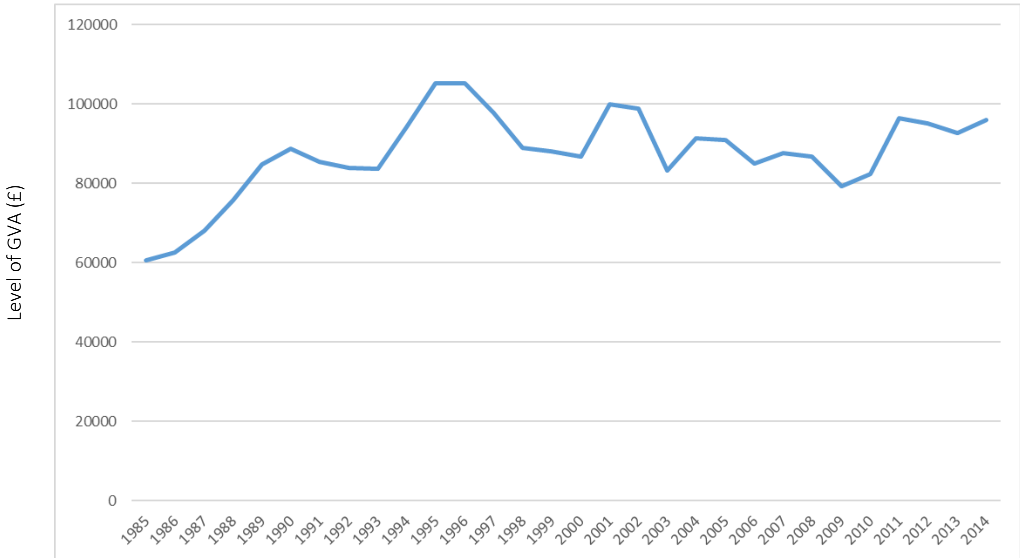

Figure 2-4 The total GVA in the GB manufacturing sector between 1985 and 2014

Source: ARD Database

The British manufacturing sector experienced a steady decline in terms of the number of plants and the level of employment between 1986 and 2014. However, in terms of total Gross Value Added (GVA), this rose over the same time period, as can be seen in Figure 2-4. Following a slight decline mid-90s to 2009, the total GVA increased from 2010 onwards and finished at a higher level when compared with the beginning of the time period in 1986.

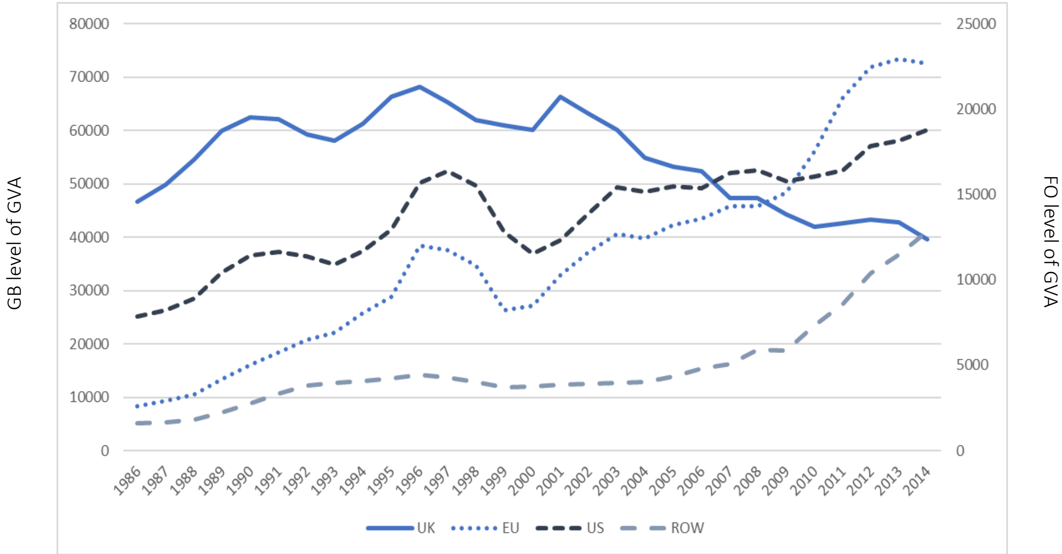

Figure 2-5 The total GVA in the GB manufacturing sector by ownership group between 1985 and 2014

Source: ARD Database

Figure 2-5 uses a three-year average, clarifying the trends in the data, and separates the GVA trend into the four different ownership groups. At the beginning of the period, every ownership groups sees an increase in the total GVA, with all but the UK-owned finishing the time period with a higher level of GVA than at the start of the time period. From 2001 onwards, UK-owned plants experienced a steady decline in GVA; this could have been influenced by foreign-owned firms buying UK-owned firms, firms thus changing category. Over the same period the other ownership groups experienced a steady increase in total GVA until the end of the period, potentially through the foreign-owned firms making efficiency savings, as well as innovating or producing higher value goods. The EU- and ROW-owned plants experienced a large increase in total GVA from 2010 onwards. By the end of the time period, the EU-owned plants had the highest level of total GVA when compared with the other foreign-owned plants, with ROW-owned plants having the lowest.

On a national scale, there was a steady decline in the number of plants and the level of employment in the British manufacturing sector over the period 1986 to 2014. However, while employment fell, the total overall GVA of manufacturing plants increased, and then remained almost stable for the remainder of the period. Efficiency savings could have contributed to this increase. Within these overall figures however, UK-owned plants saw a decline in the level of employment and the total GVA over the time period, possibly contributed to by foreign- owned firms buying up productive UK-owned plants. This decline in GVA and employment was compensated for by increases in GVA and employment in foreign-owned plants over the period, with the exception of the US-owned plants' total employment. The share of employment and total GVA of foreign-owned firms increased over the time period. By the end of the period, EU-owned plants had the highest level of employment and highest total GVA when compared with the other foreign-owned plants. In the light of these statistics, the UK's decision to leave the EU in 2016 appears to have risked reducing the investment which contributed the highest level of employment and GVA within the region, when in comparison with other foreign-owned plants. The Bank of England's analysis in 2019 and 2020 found that Brexit would reduce both productivity and investment due to increased uncertainty as well as firms having to spend more time on Brexit-related planning and paper work (Bank of England, 2020).

2.3 The North East Manufacturing Industry

The North East is a region that is known for its manufacturing heritage, as illustrated in Section 2.1 and in Box 2.1 the Timeline of the North East Manufacturing Sector. Throughout the nineteenth century it developed from its natural resources, cheap coal and iron ore, power and transport infrastructures, deep water ports, to support the growth and expansion of heavy industries. However, as these large industries declined post-World War Two, they were then replaced with chemical and plastic industries in the twentieth century. The figures below show the National and North East descriptive statistics of the manufacturing sector between 1984 and 2014, reflecting the overall decline in the manufacturing sector.

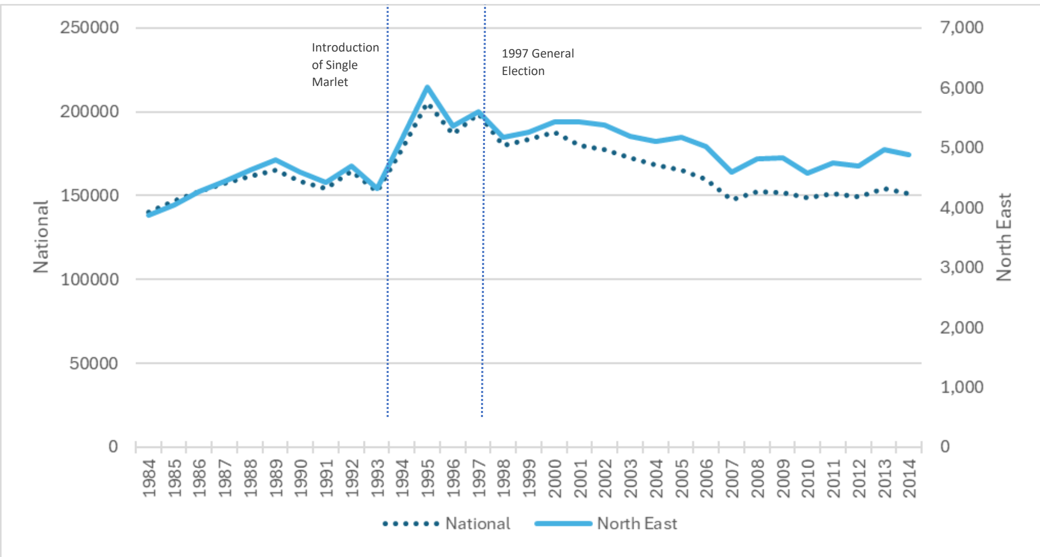

Figure 2-6 Number of manufacturing plants in the North East of England

Source: ARD Database

Figure 2-6 shows the total number of plants in the North East manufacturing sector from 1986 to 2014, a consistent time frame chosen because of the data being unimpacted by Brexit discussions. Up to and following the launch of the Single Market within the EU in 1993 the increasing trend for the number of plants in the North East follows the national trend. After 1997, the North East's trend in the decline in the number of plants is less steep than was seen in the national trend post 1997. Indeed in 2014 the North East has a higher number of plants at the end than at the beginning of the time period in contrast to the national trend.

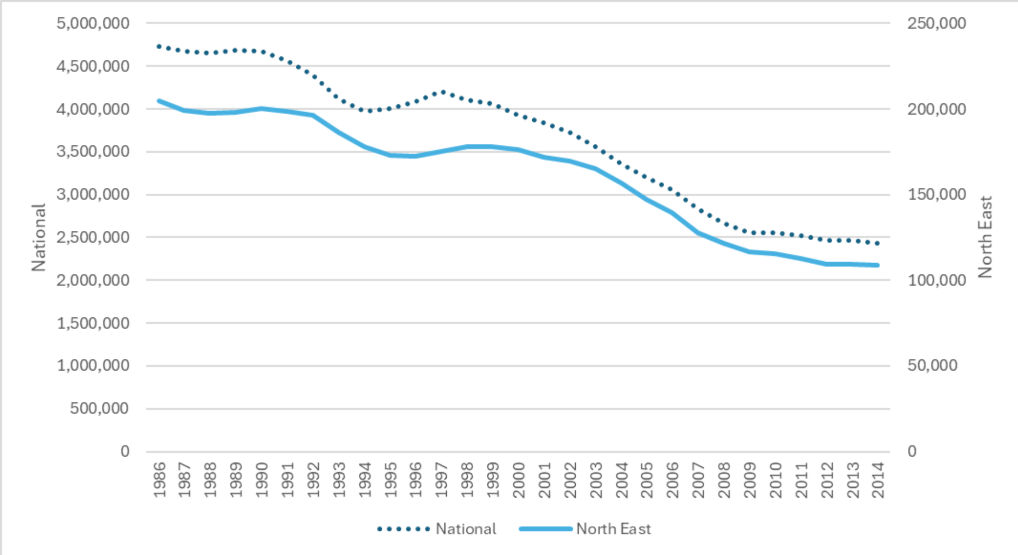

Figure 2-7 Three year average of total level of employment in the manufacturing sector in the North East of England

Source: ARD Database

Figure 2-7 shows the total employment for the North East manufacturing sector, showing a steady decline in the level of employment, mirroring the national picture, although this steady decline was not paralleled by a similar decline in the number of plants in the North East. The number of plants in the North East is greater in 2014 than in 1986, despite the level of employment falling by just over 100,000. This is potentially due to the increase in mechanisation of manufacturing or the closure of large heavy industries. These large heavy industries employed thousands of workers, and the closure of a single plant would cause a large drop in the level of total employment.

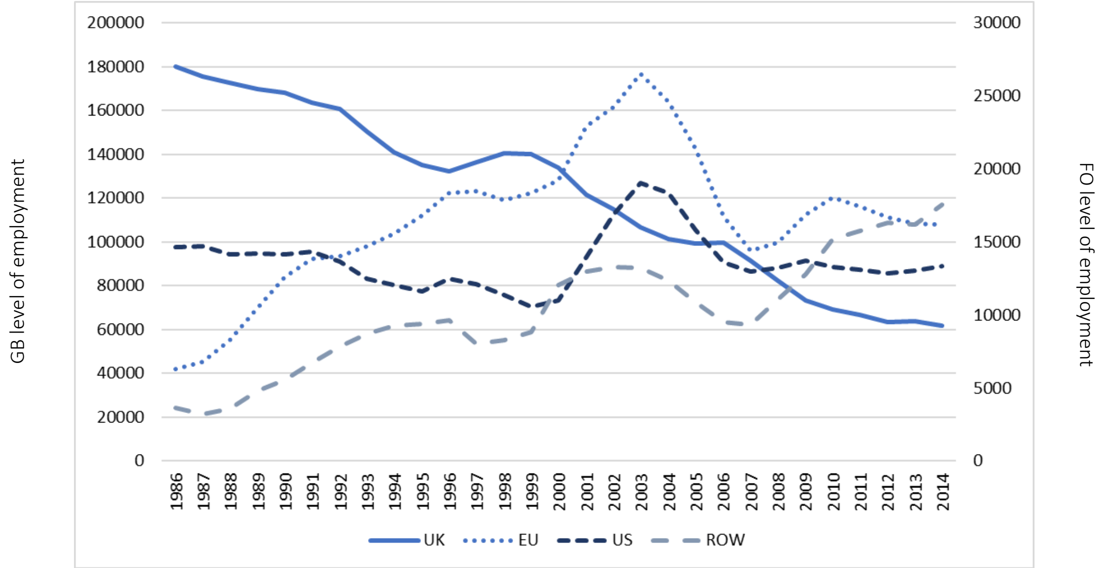

Figure 2-8 A three-year average of the total level of employment by ownership group in the manufacturing sector in the North East of England
Source: ARD Database

Figure 2-8 shows the total level of employment in the North East by ownership group using a three-year average to make the trend clear. The level of employment in North East UK-owned plants declines over the period 1986 to 2014, whereas the employment within the foreign-owned plants rises over the same period. This mirrors the national picture.

In contrast, in the North East the level of employment in US-owned plants increases over the same time period, against the national trend where the level of employment declined in US-owned plants.

The employment in EU-owned plants shows a similar trend to the national picture, up until 2003. Nationally, there was a decline in the level of employment in EU plants although it did almost recover to 2003 levels by 2010. In the North East, there was a greater decline in the level of employment in EU-owned plants, and the level did not recover to 2003 levels.

Both US- and ROW-owned plants saw an increase in the level of employment over the period, and by 2014, ROW-owned plants had the highest level of employment when compared with other foreign-owned plants.

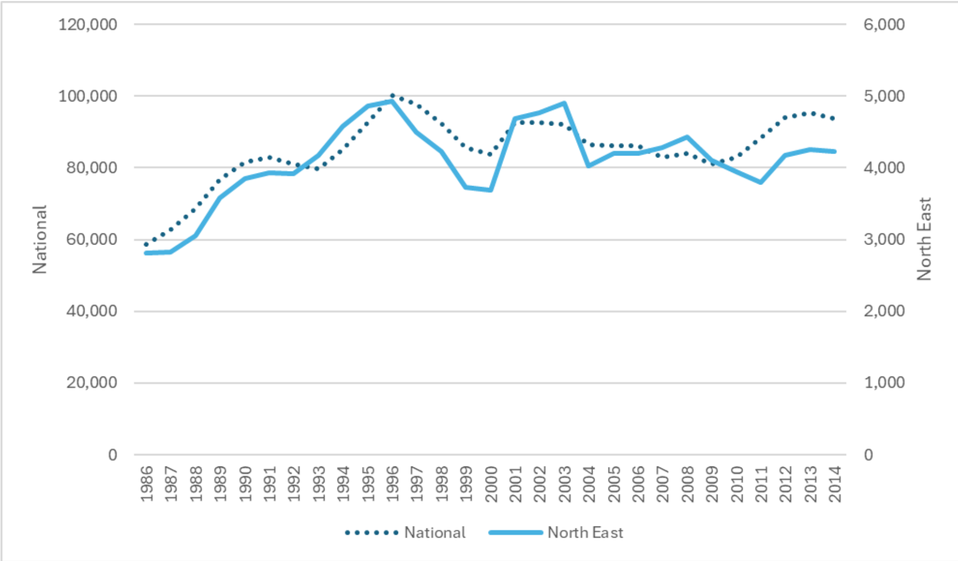

Figure 2-9 A three year average of the Total Level of GVA in the North East manufacturing sector

Source: ARD Database

Figure 2-9 shows the level of GVA both nationally and for the North East manufacturing sector. There was an increase in the level of GVA between 1986 and 2014, at the national level. There was a decline in GVA from 1997 to 2000 before it recovered to near pre-1997 levels. There was decline in the GVA in 2003 and then the trend remained relatively stable except for a slight decline over the 2008 recession, before recovering to just below 2007 levels.

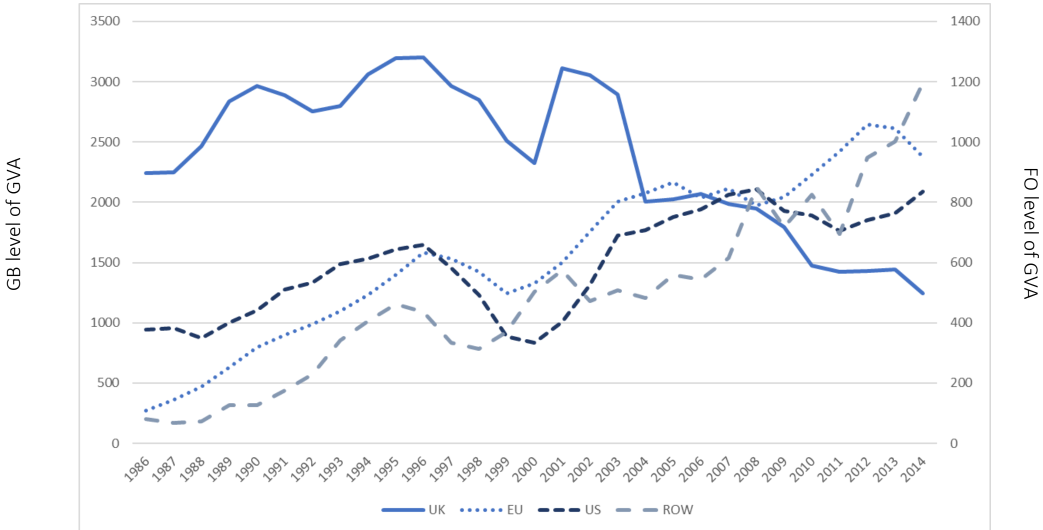

Figure 2-10 A three year average of the total level of GVA by ownership group on the North East manufacturing sector

Source: ARD Database

Figure 2-10 shows the total GVA by ownership group in the North East manufacturing sector using a three-year average over the period 1986 to 2014. The UK-owned plants experienced a decline in the level of GVA produced. The trend for GVA in UK-owned plants does not recover after 2003 and continues to decline for the remainder of the period.

The GVA within foreign-owned plants taken overall, however, increases over the same period, although the US-owned plants buck this trend and experience a similar decline to UK-owned plants after 1997, something EU and ROW plants did not experience as steeply.

The level of GVA in both EU and ROW plants increased, until ROW plants had the highest level of GVA compared with the other foreign-owned plants in the North East of England. EU plants did not experience a decline in the level of GVA in the 2008 recession, indeed their GVA increased, whereas that in both US- and UK-owned plants' declined. ROW plants level of GVA fluctuated in this time period, before increasing rapidly in 2011.

Compared with the national picture, the trends in GVA for both the UK and foreign-owned plants are similar. The UK-owned plants experienced a steady decline from 1995 onwards, and all foreign ownerships experienced an increase in the total GVA. Unlike the national picture, the ownership group with the highest level of GVA is ROW, contrasting with the national situation, where these have the lowest level of GVA. The US-owned plants have the lowest level of total GVA in the North East of England, while nationally they have the second highest amount.

2.4 Conclusion

It has been seen that the manufacturing sector has historically always been important to the North East of England, continuing into the period considered here, 1986 to 2014, even given the rise of the services sector throughout the country.

Over the period 1986 to 2014, the number of UK-owned plants declined, and there was a decline in the level of employment in UK-owned plants, as well as a decline in the total level of GVA in UK-owned plants, at both a national level and in the North East. By contrast, most foreign-owned plants, with the exception of US-owned, experienced a rise in employment, in number of plants, and in total GVA across the same time period in both the North East and nationally.

The manufacturing sector is a large employer and generates income for the North East region, and it also attracts international investment into the region, which by the end of the period 1986 to 2014 contributed a higher level of GVA to the region than the UK-owned plants, even though there were far fewer foreign-owned plants.

This was also seen at a national level, where foreign-owned plants also produced a higher level of GVA compared with the UK-owned plants by the end of the period 1986 to 2014 even though there was a higher number of UK-owned plants which had a higher level of employment. This suggests that the foreign-owned plants possessed some characteristics, such as research knowledge, working practices or technology, which UK-owned plants did not have, and which boosted productivity allowing them to compete successfully with the UK-owned plants.

To examine this further, the next section reviews the literature that discusses the impact foreign ownership can have on productivity and the impact these foreign-owned plants can have on surrounding domestically-owned plants.

3. Literature

3.1 Introduction

This chapter sets out the existing literature and knowledge base on foreign direct investment and productivity. Firstly it examines the theory and supporting studies behind the wide promotion of FDI globally, as a solution to underdevelopment and poor productivity. From these studies, the chapter goes on to consider the origin and motivation of FDI, and the impact of host country or host region characteristics on the assimilation of advantageous characteristics through spillovers. Section 3.2 examines the theory behind FDI and evidence of any ownership effect occurring due to foreign ownership. Section 3.3 presents literature examining the impact of differences in foreign ownership on productivity, and the final section 3.4 examines the presence and impact of spatial spillovers from foreign direct investment.

The conclusion identifies gaps in the literature, specifically that there are no studies focusing on productivity advantage or spillovers in the North East, relating these to FDI, and that there is little UK regional research in this area at all. The research questions which form the basis of this thesis address these gaps and look at FDI related to the North East's productivity advantage and spillovers, having created a UK manufacturing sector cluster configuration to facilitate the analysis. It also undertakes a comparison between the North East and the North of England, and South East regions. The conclusions of this work create an objective knowledge base on which future policy objectives for the North East can be set.

3.2 Foreign Direct Investment

Foreign-owned firms are argued to possess advantageous characteristics which allow them to overcome the additional costs related to setting up in a host country. These characteristics could include specialist knowledge related to production, more advanced capital, a better skilled workforce, and improved management and marketing techniques (Hymer, 1976). The International Monetary Fund (IMF) define foreign direct investment (FDI) as the investment involving a long-term relationship, which reflects a lasting interest of a resident entity in one economy in an entity that is resident in an economy other than that of the direct investor. The OECD highlighted FDI as an integral part of growth and development, especially in developing countries (OECD, 2002).

The impact of FDI in a host country can be separated into direct and indirect effects (Castellani & Pieri, 2010). Direct effects include multinational enterprises (MNEs) being more productive than domestic firms when they establish their plants in regions, due to them possessing advantageous characteristics such as those outlined above (Hymer, 1976). MNEs can also self-select into more productive industries, which can give the illusion that foreign ownership leads to higher productivity, when in fact they are simply based in more productive industries (Benfratello and Sembenelli, 2006). Indirect effects include spillovers from foreign-owned to domestic plants, either through the movement of labour or technological externalities. Because of these externalities, policy makers hope that domestic plants will benefit from the presence of foreign-owned plants and provide incentives, usually in the form of subsidies, to attract FDI into certain regions such as occurred in the North East in the 1980s with the Nissan plant in Sunderland.

The OECD highlight that while FDI can be a vital contributor to growth and development, there can be negative consequences from FDI in the host country, mainly the lack of any positive linkages with domestic plants, negative competition effects on local plants, and lack of absorptive capacity of local plants (OECD, 2002). There is no definitive conclusion on the effect FDI has in a region, or on the surrounding plants, within the literature. This section will present the theory and the literature surrounding the impact of FDI on firms within host countries.

3.2.1 Theoretical motivations for FDI

FDI as stated above can have both direct and indirect impacts on the host country. The direct impact of FDI is associated with the elements of the investment that the MNE can control (Kalotay, 2012), such as the level of training for human capital, or the affiliates under direct ownership of the MNE. The indirect impact of FDI is usually associated with spillovers originating from the presence of MNEs within the host country (Girma et al, 2015). These can take place through such things as technological transfers, vertical (backward and forward) linkages with domestic firms, and the hiring of workers who have previously worked in MNEs. These can have a positive impact on the surrounding domestically-owned plants, improving the level of productivity within these plants. However, a further indirect impact of FDI can be the competition effect, with MNEs out competing the domestically-owned plants due to lower costs, as they benefit from the unique assets that domestic plants do not. As a result, domestic plants either cut production or leave the market, reducing output and productivity within the host country (Girma et al, 2015).

While Hymer (1976) states that FDI has an outright advantage over domestically-owned plants within the host country, there are some models which suggest that FDI advantages, or a lack of these, depend on the motivation for FDI. These motivations may result in FDI being less productive than domestically-owned firms and may have a detrimental impact on the host country.

The motivations for foreign investment have been divided into two broad categories: demand side and supply side (Dhingra et al., 2018). Demand side investment aims to access the hosts' market or hosts' neighbouring market. Supply side investment aims to exploit host countries' local comparative advantage in relation to certain processes or inputs of production. Dhingra et al (2018) argue that these two categories are not mutually exclusive.

Some motivations can result in a negative impact in the host country. Reis (2001) suggested that FDI could reduce national welfare due to the returns from FDI being repatriated by the foreign investors. This was most likely to happen when foreign investors introduce new goods into the economy at a lower cost to that of domestic firms. This means that domestic firms which are unable to compete in the R&D sector are forced to leave. This has a negative effect on national income and loss in profits. Foreign investors may also choose to transfer profits away from the host country, decreasing national welfare. This transferal of profits to the foreign investors, Reis (2001) argues, is a creative destruction effect due to the lowering of costs for FDI in introducing better technologies. The only circumstances where there is not negative impact on welfare is when productivity growth is able to compensate for the loss of profits.

Driffield and Love (2007) developed a taxonomy that aimed to capture the motivations influencing the decision to invest in host countries. They include the characteristics of both host and investor countries, to establish the aim behind the FDI investment. They used R&D intensity as a measure of technology and unit labour costs as a measure of costs for the host country and the investor. This leads them to four motivations for FDI in host countries:

1) Technology sourcing/local advantage

   Where the host economy is more R&D intensive than the investor's economy and the labour costs in the host economy are lower than the investor's

2) Technology sourcing

   Named "Pure" technology sourcing due to labour costs being higher in the host economy than the investor economy. The investor is attracted to the host country by the high level of R&D intensity

3) Ownership advantage/ Efficiency seeking

   Where the investor has a higher level of R&D intensity, and the host has lower labour costs. This is a version of technology exploitation.

4) Ownership advantage

   "Pure" ownership advantage motivation, where the source country's R&D intensity is greater than the hosts. Even with higher labour costs, FDI still takes place

This model provides some insight into the motivation of firms to invest in foreign countries. Each motivation has a different impact upon the host economy.

FDI motivation by (1) would have no or a negative spillover effect on the host economy, as the investing firm lags in technology, meaning it may compete on labour costs rather than technological efficiencies.

Similarly, investment motivated by (2) would have no expected spillover benefits within the host economy due to the investing firm being unable to offer anything to the host economy.

Investment motivated by (3) has the potential to provide positive spillovers due to the more advanced technology. Yet, due to the low labour costs, firms may choose to compete on labour costs rather than share technology.

Investment motived by motivation (4) is the scenario which provides the highest level of positive spillovers because of the investor's higher level of technological advantage and the inability of the investing firm to compete on labour costs.

While useful, this taxonomy excludes other motivations that could contribute to the investor's decision to carry out FDI. These could be the locational advantages of the host country, allowing access to markets or similar industries, the host country's characteristics such as language and culture, or suitable government agencies.

Sârbu (2014) presented four motivations that influence FDI, two of which overlap with the work done by Driffield and Love (2007). The two that overlap with the work by Driffield and Love (2007) are Resource Seeking and Efficiency Seeking. Sârbu (2014) states that these motivations are normally performed by more mature firms, whose aim is to establish more permanent fixtures within host countries, in order to benefit from access to lower cost resources or labour. The other two motivations, Market Seeking and Strategic Asset Seeking, are not covered by Driffield and Love (2007) in their taxonomy. Market Seeking firms look to establish into locations that give them better access to local or regional markets, as well as suppliers. Strategic Asset Seeking is where multinationals invest either on their own or with a partner to maintain international competitiveness. Sârbu (2014) clarifies that these motivations are not independent of one another, and that a firm may be motivated by more than one of the categories.

Zitta and Powers (2003) presented two reasons for FDI: Factor Seeking, whereby the investor is seeking to access resources to contribute to the firms' foreign operations, and Market Seeking, whereby the firm is seeking a market where it is possible to sell their products. Zitta and Powers (2003) suggest two motivations behind these reasons: external market factors and internal company reasons. The market factors include human resources availability, market size, political climate, and capital markets. The internal factors stem from the firm's objectives, whether that be an aim to increase growth, profit, and have better access to technology, or to increase their global standing.

Dunning , 1988) proposes a three legged approach, the Ownership, Locational, and Internalisation (OLI) advantages theory, which encompasses the motivations mentioned above by the different theories. Wilson and Baack (2012) suggested that the three variables are often portrayed as the "Why", "Where", and "How" of FDI decision making. The Ownership advantages are the 'Why' motivations, the Locational component is there 'Where' motivation, and the Internalisation is the 'How' motivation. Ownership represents the unique skills and assets the MNE possesses to overcome sunk costs associated with establishing plants abroad, as outlined in Hymer (1976) who stated that the foreign-owned firms must have an outright advantage over the domestic plants to be able to compete within the host market. The Locational motivations are the advantages linked with investing in certain regions. This could be to have access to specific markets, access to resources, or have efficiency seeking or asset seeking motivations.

Sârbu (2014), as stated above, separates motivation into two groups: Market Seeking and Strategic Asset Seeking to allow for more precise identification of a firm's FDI motivation. Driffield and Love's (2007) taxonomy, as stated, also overlaps with this motivation. The final motivation, Internalisation, is the firms' ability to withhold their advantages to prevent spillovers. This means they can maintain their advantage over the domestic firms within the host country.

Nguyen, Duysters, Patterson, and Sander (2009) present the Photosynthesis model, which states that to receive any benefits from FDI, the host country needs to reach a certain level of absorptive capacity. If the country does not reach this level of capacity, then they do not benefit from the FDI. Nunnenkamp (2004) also suggested that host countries should reach certain levels of development to be able to extract benefits from FDI. The following papers highlight how host countries' characteristics can impact upon the effect of FDI has on economics growth or TFP.

FDI theory suggests that with the presumed advantages and unique assets MNEs possess, they are expected to perform better than domestically-owned plants within the host country. The literature suggests that the impact of the FDI on productivity within in the domestically-owned plants depends on the motivation for the FDI. Where the aim is to integrate into a market, either to access the unique assets or gain access to the market, the presence of FDI can be positive. Host countries benefit from the FDI either through supply side linkages with domestic firms, the training of native workers, or undertaking R&D within the host country. However, if the MNE can withhold its assets or chooses a host country due to its lower costs of land or labour, this would have a negative impact within the host country and could be seen as a drain on the host economy.

3.2.2 Cross-country analysis of the impact of FDI

With the economic theory suggesting that host economies can benefit from the presence of foreign investment, the IMF, World Bank, and the OECD highlight and champion FDI to boost economic growth and economic development, especially within developing countries. Due to this, many countries, both developing and developed, incentivise FDI within their economies, to benefit from the advantageous characteristics. However, the research above indicates how complexities of motivation mean that host countries do not always benefit from the presence of FDI, for the reasons outlined.

Lee (2007) found that FDI has a positive impact upon host economies when using panel data from nine OCED countries in a positive long term relationship between FDI and productivity in the host country. Xu, Liu and Abdoh (2022) found in a cross country study of 139 countries, strong and robust evidence of that foreign ownership is positively related to firm productivity, with those countries with medium institutional development being able to capitalise more, when compared with those countries with low or high institutional development. Gopinath et al (2003) found FDI had a positive impact on wages across 26 developed and developing countries, however also found that FDI can widen the wage gap between skilled and unskilled labour. Pasali and Chaudhary (2020) found from both developing and developed countries that firms with foreign ownership had a slight performance advantage.

Demonstrating that the effect of FDI within a host country is not always positive, some studies found that FDI either had no effect or had a negative impact upon the host country. Meniago and Lartey (2021) used a cross country analysis for Sub-Saharan Africa between 1980 and 2014 and examined the direct and indirect impacts of FDI on economic growth. They found the direct effect of FDI was negative on both economic growth and TFP, while the indirect effects were insignificant. While the use of cross-country analysis can provide an overview of the impact of FDI, due to the aggregation of the data, it fails to capture the variations within each economy. This is shown by Bitzer et al (2005) analysis which examined the effect of inward and outward FDI across 17 OCED countries. They found the positive effect of FDI was not consistent across the 17 countries, while outward FDI had a negative impact on productivity. The literature indicates that accruing the positive impact of FDI for a host country is more complex than some of the theories in the previous section initially suggested.

Like Bitzer et al (2005), Herzer (2012) found inconsistencies in the impact of FDI within a host country. On average, he found FDI had a negative impact on growth in developing countries. However, this impact varied greatly across countries, suggesting that cross-country heterogeneity in growth can be explained by cross-country differences.

Herzer and Donaubauer (2018) found that the characteristics of the host countries influenced the impact of FDI on TFP within that country. They examined the long-term effect of FDI on TFP in 49 developing countries between 1981 and 2011 and found that, on average, FDI had a negative impact on TFP over this longer term. However, when they tested the impact of FDI on productivity in subgroups of countries, based upon characteristics, there were times when FDI had a positive impact on TFP. In countries with higher levels of financial development, FDI had a positive but insignificant impact on FDI. In those developing countries with a higher level of human capital, financial development, and trade openness, FDI had a significant and positive impact on TFP.

The differences in the impact of FDI due to the host countries' characteristics can be seen in a number of cross country studies. Cipollina, Giovannetti, Pietrovito, and Pozzolo (2012), using a disaggregated panel dataset of 14 manufacturing sectors from developed and developing countries between 1992 and 2004, found that the impact of FDI on a host countries' growth was positive. The impact was stronger in more capital-intensive and technologically advanced sectors. This increase in growth is primarily due to an increase in TFP and the growth of factor inputs.

Similarly, the work by Amann and Virmani (2014), examined the role that the flow of FDI (inward and outward) had on TFP in emerging economies, across 18 emerging economies and 34 OECD countries. They found that FDI enhances productivity growth, but had more of an impact when R&D intensive, developed countries invested in emerging economies.

Al Nasser (2010) also found that host countries' characteristics influenced the impact of FDI within Latin American counties. They found that FDI had a positive interaction effect where a larger technology gap was present, but a negative impact on growth with level of school attainment, possibly because of varying educational attainment levels across developing countries, and the limitations on the ability to assimilate advanced technology in a poorly educated workforce.

Unlike Herzer (2012) and Herzer and Donaubauer (2018), these studies found that the overall impact of FDI is positive. The host countries' characteristics influenced the impact of FDI, for example where the host has greater R&D intensity or is more technologically advanced. Borensztein, De Gregorio, and Lee (1998), again found across investment from industrial countries to 69 developing countries that host countries' characteristics impacted upon the effect FDI has on productivity, related to the host country having a minimum threshold of human capital stock. They suggest that FDI contributes more to economic growth than does domestic investment. FDI also appears to increase total investment in the host economy, suggesting a prevalence of complementary effects with domestic firms. However, only when the host country reaches a threshold level of human capital does it benefit from the presence of FDI.

Fu (2008) used Chinese data to examine the impact of FDI on regional innovation, with a focus on the role of absorptive capacity and complementary assets. They found that FDI had a positive contribution to the overall regional innovation capacity, yet the strength of the effect was again dependent on the region’s characteristics, such as the level of absorptive capacity and innovation-complementary assets in the host region. Borensztein et al (1998), found that the more advanced, usually coastal areas of China, possessing high levels of skilled labour, R&D activity and where the top universities and research institutes are located, benefited the most from FDI in comparison with the inland areas which received lower valued FDI, resulting in fewer, if any, positive spillovers.

The work by Fu (2008) and Borensztein et al (1998) in China could relate to the taxonomy proposed by Driffield and Love (2007) regarding the impact of different groups and motivations of FDI impacts on the host region. The coastal regions in Fu(2008) were more likely to attract high value FDI, which could result in more positive spillovers to local firms, whereas in the inland regions, the FDI attracted is low value and does not result in as many, if any, positive spillovers. In Borensztein et al (1998), those regions that surpass the minimum human capital threshold are perhaps more likely to attract higher quality FDI when compared with those regions that do not. For those regions to benefit from FDI, the absorptive capacity needs to be increased. However Fu (2008) points out that this takes time and may create a ‘bottleneck’ which prevents regional growth.

A further factor to be considered regarding the effect of FDI is the time elapsed following the investment. The negative impact of FDI usually arises from more advanced FDI crowding out the domestic firms. Adams (2009) found that FDI in Sub-Saharan Africa in the short term had a negative impact on domestic investment. However, in the long term it had a positive impact on this domestic investment, suggesting in the short term FDI caused crowding out of domestic investment within the host country, but over time this is more than compensated for by the FDI investment.

Dinh, Vo, The Vo, and Nguyen (2019) examined FDI and its impact on economic growth in developing host countries in both the short and long term. They also found in the short term, FDI had a negative impact on economic growth, possibly suggesting crowding out by foreign-owned plants, while in the long term it did help stimulate growth. They also highlighted that other macroeconomic factors can have an impact, suggesting that encouraging FDI alone will only partly boost economic growth.

Most cross-country studies state that FDI can have a positive impact on the host countries' growth or productivity, and this is the main reason why the IMF, World Bank, and OECD champion the use of FDI within developing countries. However, among several factors that impact upon the effect FDI, time after investment is valuable to include within analysis, as it appears that, in the short term, impact can be negative, but be more positive over the longer term.

The important factors which influence the impact of FDI are the host country or region characteristics and absorptive capacity as well as FDI motivation and characteristics. The benefits expected from FDI will only occur if the host country is able to capitalise on the investment, whether that is through the appropriate level of human capital or technology capacity. The Driffield and Love (2007) taxonomy states that the motivation of FDI can influence the impact it has on the host region, depending on the characteristics of the host region or country. The research by Fu (2008) into regional differences in China and Borensztein et al (1998) into the human capital threshold suggests that the high value FDI is attracted to and based within regions that possess high skilled labour, and high level of R&D activity and research, while low value FDI is attracted to and located within the less developed inland regions.

Winkler (2013) used data from a number of developing countries[6] from around the world to evaluate any differences between domestic and foreign investors in terms of generating positive spillovers to local suppliers and firms in the host country. Overall, they found that foreign-owned firms outperformed the domestic firms in terms of sales, firm size, productivity, exporting behaviour and direct export share. However, they were less intertwined with local suppliers and the surrounding firms, in terms of using fewer domestic inputs and local workers. They separated ownership groups into two groups: Sub-Saharan Africa (SSA) and Asian. They found that investment from SSA was more likely to assist the domestic suppliers and sell a higher share of their output to the local market. Asian investors also sold a high share of their output to local markets however were less likely to assist local suppliers.

3.2.3 The Micro level impact of FDI

The macro studies in the previous section show that the influence of FDI is not uniform across all countries. This could be due to the motivation of the FDI, the characteristics of the host country, or the characteristics of the FDI. Micro data allows for these differences to be accounted for as it can

[6] The countries used are Chile, Ghana, Kenya, Lesotho, Mozambique, Swaziland, and Vietnam

consider the heterogeneity within countries. This section examines the literature that uses microdata to analyse the impact foreign investment has within countries.

The use of microdata allows Khawar (2003) to specify certain characteristics, such as ownership groups within a country. They compared domestic and foreign ownership in Mexico for the year 1990. The direct effect is both positive and large, meaning foreign firms were more productive than domestic firms. The author states this could potentially result in positive spillover benefits resulting from technology transfer; however, they found no evidence that any existed. This could be due to the short time period covered by the analysis as this study is based on data from one year. It can take time for foreign firms to integrate into the domestic market, and for domestic firms to assimilate the foreign technology. Kosova (2010) found that in the medium to long term, domestic firms had time to adapt to the foreign presence.

Girma et al (2015) examined the direct and indirect impacts of FDI within China using firm level manufacturing data over a two year period, 2004 to 2006, using 2005 as the treatment year for foreign ownership and comparing this to the pre-treatment year of 2004 and post treatment year of 2006. They used industry-region clusters, with an average proportion of foreign firms within each cluster at about 21 percent. Overall, they found a positive direct effect from foreign ownership, however the proportion of foreign ownerships within the cluster changed the impact. The higher the level of foreign ownership, the greater the benefit of the foreign ownership. This could suggest that foreign-owned firms benefit more from other foreign ownerships rather than other domestic plants and would result in the domestic plants being crowded out. The indirect influence of foreign ownership, such as spillovers, negatively impacted upon domestically-owned plants, because of what Girma et al (2015) presumed to be the competition of market-stealing effects.

A potential reason for these findings, as in the case of Khawar's study (2003) above, is that the short time period used for the analysis could have failed to capture the indirect impact of foreign ownership which the literature indicates is seen to take place over the longer term within the host country. The cross country studies by Adams (2009) and Dinh, Vo, The Vo, and Nguyen (2019) both highlight that in the short term, the presence of FDI can have a negative impact, while in the long term it can help stimulate growth and productivity.

The cross-country studies above suggest that both host country characteristics, and FDI motivations, influence the impact FDI has within in a host country, and this is also found on a micro data level. Konings (2001) suggested that host country characteristics impacted on the effect of foreign ownership on productivity in the three emerging economies of Central Europe: Poland, Bulgaria and

Romania over a four year period, 1993 to 1997. They found that only in Poland did FDI have a positive impact on productivity. FDI had no impact in Romania and Bulgaria, countries which, according to Konings (2001), have less advanced economies when compared with Poland. Konings (2001) also suggests that the competition effect, where FDI outcompetes the domestic firms, maybe the more dominant effect in Romania and Bulgaria, forcing the domestic firms out of the market.

Hayakawa, Lee and Park (2013) also examined the influence host country characteristics (mainly focusing on host country wages) have on FDI, using firm level data from three Asian countries: Japan, Korea and Taiwan. Using the theory presented by Yeaple (2009)[7], they examined how wage levels impacted upon the level of outward and inward FDI. They found that a high wage level in the home country had a significant and positive influence on the number of investors. A 10% percent increase in home country wages increases the outward investment by 25% yet decreased the level of inward investment by 1.5%. Using a wage ratio of host country wage to home country wage, giving the host country as having lower wages than the FDI country of origin, resulted in a negative impact from the investment. This suggests that a low host country wage level has a negative influence on the impact FDI. It would appear that the priority for such investors is to efficiency save on labour costs, rather than contribute to the scenario which provides the highest level of positive spillovers for the host country, by introducing higher levels of technological advantage, without the investing firm competing on labour costs.

If firms are incentivised to invest due to low wage levels in the host country, Driffield and Love (2007) suggest that the presence of FDI can have no effect, or a negative effect, on that host country, because these firms having chosen to compete on efficiency savings, rather than introducing technological advancements. Incentivising FDI on this motivation does not provide any technological advantages for the host country, contradicting the international bodies that encourage FDI for development and growth. The failure to attract the "correct type" of FDI could be damaging for the host country, especially if it encourages a "race to the bottom" mentality.

When it comes to FDI firms establishing themselves within a foreign country, rather than building new plants, many opt to buy pre-existing plants or firms. Because of this, it has been suggested that foreign-owned plants and firms do not gain their advantages from the benefits of foreign ownership, but

[7] Yeaple (2009) states the most productive firms will invest in the least attractive countries, while the less productive firms will invest in more attractive countries, especially in terms of wages in both the host country and the home country.

rather because these foreign firms have taken over the more productive domestic plants, in a process known as known as “cherry picking”.

Guadalupe, Thomas, and Kuzmina (2012) used Spanish manufacturing panel data between 1990 and 2006 to analyse both selection and technology decisions made by multinational firms. They found that those domestic firms that were the most productive within the industry were selected for acquisition by the multinational, confirming again that foreign firms, when investing, “cherry pick” the firms they acquire. However, even when controlling for selection, there was an increase in sales, labour productivity and TFP following the acquisition. Regarding productivity-enhancing innovations after acquisitions, after controlling for firm fixed effects, they found improvements in firm technology, as firms are likely to engage in process innovation and production innovation. These firms are also more likely to assimilate foreign technologies, suggesting a technology transfer from the parent company to the new subsidiary. Guadalupe, Thomas, and Kuzmina (2012) also suggest that after acquisition, new technology and new ‘knowledge[8]’ are introduced simultaneously, rather than sequentially.

Arnold and Javorcik (2009), using Indonesian manufacturing data, also found that better performing domestic plants were more likely to be selected for foreign acquisition, and that the foreign ownership results in better performance, possibly due to better managerial and organisational changes being introduced. Arnold and Javorcik (2009) also examined foreign privatisations, where foreign ownership accounts for at least 20% of a previously publicly owned plant. Foreign-owned privatisations perform better than domestic privatisations. However, while foreign privatisations differ in skill composition and wage rate when compared with domestic plants, they do not result in higher employment, unlike foreign acquisitions.

These studies suggest that even with foreign-owned firms selecting the more productive or advanced domestic plants, the acquired firms still benefit from the foreign ownership either through technology transfer or by being introduced to new managerial or organisational techniques. Foreign-owned firms could be selecting these advanced domestic plants so that they are able to effectively introduce their new technology into a manufacturing facility which is able to assimilate it, otherwise it would not be possible to transfer technology efficiently from the parent company to any newly acquired plant.

Unlike Guadalupe et al (2012) and Arnold and Javorcik (2009), Benfratello and Sembenelli (2006) found that, after controlling for heterogeneity, simultaneity and measurement errors, foreign

[8] Examples of this being new information regarding new technology introduced, or the introduction of new organizational methods and techniques

ownership had no impact on TFP within manufacturing plants in Italy. Instead, they state that foreign firms are more likely to set up in the more high-tech industries and have greater labour productivity when compared with domestic plants. When this was controlled for, ownership had no impact on TFP.

Salis (2008) also found that foreign acquisitions of manufacturing plants in Solvenia had no significant impact on productivity for up to two years following a takeover. They also found that foreign acquisitions were more likely to take-over enterprises with higher productivity, were more inclined to export and were based in areas with a concentration of such industries and once controlling for this, foreign acquisitions resulted in no significant impact on productivity. Stiebale and Reize (2011), when examining the effect of cross-border mergers and acquisitions on innovation within the target firms in Germany, found that foreign ownership had a negative impact on propensity to innovation and R&D expenditure after controlling for firm endogeneity and selection bias.

The following studies examine the impact of foreign ownership in the UK. Schiffbauer et al. (2017) examined the causal relationship between foreign mergers and acquisitions (M&A) and productivity in the UK between 1999-2007. Previous studies highlighted that foreign firms tended to “cherry pick” firms giving the perception that foreign acquired plants are more productive when, in fact, they are simply based in more productive industries. They highlight this as a possible explanation of the productivity advantage. Schiffbauer et al. (2017) also found significant industry heterogeneity of M&As on productivity, but not any long-term aggregate effect. They found productivity gains were linked to those acquisitions based within R&D intensive industries, and these gains were less so within marketing-intensive industries. They also found that the effect of the M&A is dependent upon the characteristics within the domestic firm and the foreign investing firm.

Davies and Lyons (1991) examined whether foreign-owned plants possessed a productivity advantage in the UK manufacturing industry and where any such advantage originated. They examined the structural effect, where firms self-select into more productive industries, and the ownership effect, where the foreign-owned firms possess different characteristics which make them more productive than domestically owned plants. They found that no more than half of the foreign-owned firms’ advantages came from structural factors. Foreign-owned firms were more likely to select and acquire already productive industries, giving them an apparent advantage over the domestically-owned plants. Davies and Lyons suggest this could be due to their definition of ownership, but there are other studies which also find similarly that foreign-owned plants are more likely to self-select into more productive industries.

Girma and Görg (2007) examined whether productivity growth in foreign firms stemmed from technical change or scale effects, using two industry groups which are estimated separately: UK electronics, and the Food and drinks industry between 1980 and 1994. They found that any positive foreign ownership effect due to ownership change was due to technical efficiency rather than scale effects, contrasting with the results of Davies and Lyons (1991). They also found that the level of TFP within the domestic plant before acquisition played an important role in the transfer of technology from foreign parent companies to the newly acquire domestic plant, as in the results of Schiffbauer et al (2017), and found further that the productivity effect persisted through time.

In previous work, Girma and Görg (2003) examined the effect of foreign acquisition on plant survival and employment within the same industries over the same time period. They found that the foreign acquisitions reduced the lifetime of the acquired plants in both sectors, and there was a reduction in employment, especially for unskilled workers, within the electronics industry. If the previous work suggests that TFP is based upon technical change rather than scale effect, then a reduction in less skilled workers within those plants could be expected. However, this was not found in the less technically advanced and less technologically reliant food industry.

Across both macro and micro studies, FDI has been found to have both a positive and negative impact on productivity. Heterogeneity across the countries used within the macro studies had an impact on the findings of the effect FDI can have. Heterogeneity was also a factor when examining FDI impact on a micro level, where regional or firm characteristics can impact on its influence.

3.3 The direct and indirect impact of the origin of FDI

In specific circumstances, where the FDI is not primarily motivated by efficiency savings resulting from such things as the exploitation of low wages, low land costs, and weaker regulation, FDI can be shown to have a positive impact on the host country. The previous section however indicated that the FDI can also have either no impact or a negative impact within the host country, where these are the FDI motivations, or where the host country's characteristics include limited technology, low skilled labour, and poorer management practices, preventing it from assimilating the advantages brought by FDI. These latter findings contradict the seeming widespread consensus that FDI has a positive impact on developing host countries due to the positive characteristics it possesses.

Several cross country and micro level studies confirm that FDI can have either no or a negative impact within the host country, some showing that the host country characteristics are a reason for this. The host country characteristics therefore play an important part in the impact FDI has within the host country

On this basis it is reasonable to investigate whether the country of origin of FDI investment similarly influences the impact FDI investment on host countries. The following papers have separated FDI investment into different ownership groups to examine whether the origin of FDI effects the direct or indirect impact of FDI within a host country.

3.3.1 Direct impact of the origin FDI

Globerman, Ries and Vertinsky (1994) when they controlled for plant characteristics in Canada, found that foreign-owned plants had no advantage over the domestically-owned plants. However, they also found that the nationality of a firm was important. They concluded that nationality differences explain the differences in labour productivity. They also found that over time, there was not a convergence in productivity levels between Canadian-owned firms and foreign-owned firms.

Doms and Jensen (1998) found, when comparing foreign multinationals with domestic plants in the US manufacturing sector, that foreign-owned plants were more productive, had a greater level of capital and, generally, paid their workers higher wages, when compared with domestically-owned plants. However, they argue that directly comparing foreign-owned and domestically-owned firms is not a fair direct comparison. A more accurate comparison would be between domestic multinationals and foreign multinationals. They found US multinationals had the highest level of productivity, were larger, and had more capital and paid higher wages, followed by the foreign-owned multinationals and then the domestically oriented firms.

It would appear there is a hierarchy of performance, the most effective being domestically-owned multinationals, followed by foreign-owned multinationals, both outperforming domestically oriented plants. Foreign multinationals have characteristics which enable them to establish a base abroad and be competitive. Despite this, when compared with domestic multinationals they are less productive. Globerman et al (1994) also found US multinationals were more productive; these were US multinationals based within Canada.

Like Globerman et al (1994), Aitken and Harrison (1999) found foreign-owned plants did not have an advantage over domestic plants. However, they did find that plants jointly owned by a foreign firm and a domestic firms had greater productivity levels than solely foreign-owned plants in the Venezuela manufacturing industry. These jointly owned firms enjoy “the best of both worlds”, they have access to the foreign owner’s knowledge and capital, as well as the domestic knowledge of culture and supply chains. This could well be happening regarding multinational firms within the US manufacturing industry as found by Doms and Jensen (1998).

The following papers examine the impact of different ownership groups within the UK. Oulton (1998) found within the UK manufacturing sector that different ownership groups had different labour productivity. US-owned establishments' value-added per employee was 55% higher when compared with domestic firms, with the value-added per employee being 25% higher in Non-US owned establishments. These differences are suggested to stem from the differing characteristics within the foreign-owned plants. Workers in US-owned establishments have 54% more capital invested per employee than in UK establishments and Non-US workers have 47% more capital.

Conyon, Girma, Thompson, and Wright (2002) also found differences in ownership groups (US, EU, and other) in terms of wages and productivity, after foreign acquisition of a domestic plant in the UK manufacturing industry. Across all ownership groups there was a 3.44% wage premium and a 14% improvement in labour productivity following a foreign acquisition. US-owned firms have the highest improvement in productivity when compared with the other ownership groups. Comparing different ownership groups with each other (US, EU, and other) showed an improvement in productivity following acquisition across all ownership groups, with the greatest increase being in US firms, followed by EU- and the other foreign-owned. There is also a difference in wage premiums; US-owned firms had the highest wage premium (4.7%), followed by other foreign firms (3.2%). Although EU-owned firms also had a wage premium of 3.9%, this proved statistically insignificant. They found when controlling for productivity, these wage effects disappeared. They also found that with domestic acquisitions, when there was a horizontal take-over or merger, this related to a pay cut for workers, *ceteris paribus*. This was persistent even when productivity was controlled for.

Criscuolo and Martin (2009) found that US MNEs were the most productive when compared with other MNEs in the UK. Like Globerman et al (1994), however, this was not linked to "home advantage" and more linked to self-selection into more productive industries. US MNEs were more likely to operate in highly productive industries, as well as having the tendency to cluster in regions that possess geographical advantages. British MNEs showed similar levels of productivity to other foreign-owned MNEs and were more productive than those firms which did not invest abroad.

Harris and Robinson (2003) studied a group of 20 industry types and found that, when examining the level of productivity in foreign-owned plants in the UK Manufacturing sector, different ownership groups outperformed UK-owned plants. However, this was not an outright advantage but varied depending upon the industry type hosting the foreign-owned plant. They also found variation within industry types; in some industries, foreign owned plants did not perform better, or indeed performed worse, than UK-owned plants. Harris and Robinson (2003) also found US-owned plants outperformed UK-owned plants within most of the industries studied, but in a substantial minority, eight out of the twenty industries, they found no significant advantage over UK-owned plants. This could suggest that US-owned plants establish within industries where they already possess an advantage, being selective, and “cherry picking” the industries where they are able to use their home advantage. The advantage, however, appears to diminish over time as either UK-owned plants assimilate the US-technology through spillovers or US-plants do not undertake productivity enhancing technologies over the long term.

There was no clear productivity advantage found for EU-owned plants. In four industries EU-owned plants had a higher level of productivity when compared with UK-owned plants, but the EU-owned plants performed significantly worse in two further industries, although they were closing the gap with the UK-owned plants within one of those industries.

Old commonwealth[9] countries did better in three of the studied industries and worse in two, as well as showing declining performances when compared with UK plants within two further industries. South East Asian[10]-owned plants performed significantly better in two industries but significantly worse in three others.

It would appear foreign-owned plants do not have an outright advantage over domestically-owned plants across all industries. They outperform domestically-owned plants in certain industries, perhaps industries where they already have an advantage in their home county. The foreign-owned plants which are seen to perform worse than the domestically-owned plants may have chosen to establish themselves in locations where they identify they can benefit from the presence of UK- or other foreign-owned plants within the same industry. They seek to do so by assimilating technological or other advantages from these UK- or other foreign-owned plants thus boosting their own performance. This corresponds with Driffield and Love (2007) who suggest that sometimes the motivation of foreign investment is to benefit from the knowledge of domestically-owned plants. In this case, as the foreign-owned companied are less advanced when compared with the domestically-owned plants, and they are unable to contribute to increased industry productivity. The finding that some foreign-owned plants are catching up with the domestic plants in performance terms could be an indicator of this.

A study by Harris (2002) found differences in ownership impacted in terms of productivity in the UK manufacturing sector, finding for example that the US-owned plants performed better in Pharmaceuticals, and Electronic Data and Processing Equipment, as did the EU-owned plants,

[9] Comprises Australia, New Zealand, Canada and South Africa
[10] Japan, Taiwan, Hong Kong, South Korea, and Malaysia

although this EU better performance was not statistically significant. UK-owned plants performed better than the EU-owned plants in the Aerospace industries in both the long and the short term. The US-owned plants had a slight advantage, but this was not significant. In the Miscellaneous Food Industry, US-owned plants had a significant advantage over UK-owned plants, whereas the EU-owned plants had an ownership advantage but, again, it was not significant.

More recent studies by Harris and Moffat (2015, 2017) also found that different ownership groups had differing impacts on productivity. Harris and Moffat (2015) stated that this was most obvious within US-owned plants. This was replicated in Harris and Moffat (2017) where the US brownfield plants had an outright productivity increase in all sectors, both in manufacturing and services, and the same was seen in most sectors for US greenfield plants. EU brownfield manufacturing plants had a productivity advantage in all sectors, while EU greenfield manufacturing plants had an advantage in all but one.

The differences in the performance outcomes from the ownership groups could potentially be due to the cultural differences between domestic workers and the foreign ownership, rather than through technological advantages or, in some cases, seeking to gain from domestic plant technological advantages. Dunning (1988) found that cultural differences between owner and domestic workers could have a detrimental impact upon productivity. He found US-owned plants in the UK in the 1950s saw a fall in the level of productivity due to management failing to recognise the cultural differences between UK and US firms. This is similar to the findings of Doms and Jensen (1998), who found that firms which have both a foreign and domestic presence perform better than those that are solely foreign-owned or solely domestically-owned.

3.3.2 Indirect impact of FDI Origin

The previous section examined the literature addressing the way in which ownership type can directly impact plants and makes comparisons between foreign-owned and domestically-owned plants in varying contexts. The literature however does not examine the way in which different ownership groups have indirect impacts on surrounding plants, especially domestically-owned plants. One of the main incentives for FDI within a host county is for domestically-owned plants to assimilate technology and knowledge in order to increase growth and productivity within those plants. However, as can be seen in the literature below, this is not always the case.

Zhang, Li, Li, and Zhou (2010) found a positive relationship between the diversity of FDI and productivity within the Chinese manufacturing industry. They also found the larger the domestic firm, the greater the effect of FDI, and the effect was the greatest when the technology gap between FDI and the domestic firm is at an intermediate level. The different countries of origin of FDI present a variety of technologies and managerial techniques that the domestic firms can assimilate, but their ability to do so is dependent upon the domestic firm's characteristics.

While Zhang et al (2010) found an overall positive relationship between domestic and different foreign ownership groups, Azeroual (2016) found that different ownership groups can result in a negative impact on TFP within the Moroccan manufacturing industry. When comparing investment from Spain with investment from France, Spanish investment had a positive impact on TFP while French investment had a negative impact on TFP. This effect was more obvious in medium and high-level technology classifications. Azeroual (2016) suggested that the negative impact on TFP can be as a result of the productivity gap between domestic and French companies, the French firms' investment rate and ability to control technology transfer. This suggested that domestic plants were unable to assimilate the technology and knowledge from French firms, whereas they were able to do so from the Spanish firms, either through spillovers or by FDI investors sharing knowledge with Moroccan firms. It may also have been the case that investing French firms were better at withholding their technological advantage than the Spanish firms.

Similarities in characteristics between the host country and country of origin can influence the impact FDI within the host country, as seen by Schiffbauer et al. (2017) in the UK. Wang, Gu, Tse, and Yim (2013) looked at FDI from countries that were ethnically similar in origin into Chinese cities between 1999 and 2005. They proposed that ethnicity-linked FDI would share similar characteristics to the domestic plants, have stronger local embeddedness, and thus could reduce the negative impacts of FDI. However, they also argue it could also potentially limit the positive effects of FDI which were found to be correspondingly greater from non-ethnicity linked FDI. More ethnically diverse investment could bring distinct advantages and superior resource pools and managerial processes. There is also less incentive to duplicate R&D and other investments near to FDI originating locations.

Wang, Gu, Tse, and Yim (2013) results confirmed that the non-ethnically similar firms possessed superior practices and resources, but that they were also less embedded into the economy. The positive influence of the non-ethnically similar FDI was stronger when the institutions in the cities were stronger, for example stronger contract and property rights protection. The ethnic-linked FDI was more adaptive to the local environment, but there were fewer positive spillovers, and it had less of an impact on domestic firms' productivity.

Monastiriotis and Alegria (2011) also examined how FDI impacted on domestic productivity in Bulgaria, focusing on Greek FDI, due to its regional similarities with the Bulgarian economy. They found that

Greek-owned firms generated substantial and greater spillovers compared with spillovers from other European nationalities. Spillovers were concentrated within “less dynamic parts” of the economy, mainly small manufacturing firms, and labour-intensive and low-tech industry sectors. They found that spillovers from other European countries were smaller, yet more uniform across sectors and firm groups.

Some have examined the direct of FDI spillovers from different ownership groups. Javorcik and Spatareanu (2011) used data from the Romanian manufacturing industry to examine the link between the origin of foreign investment and the degree of vertical spillovers related to the investment project. They found that there is a positive association between US companies in the downstream sectors and the productivity of the supplying Romanian firms. However, there is no evidence that the presence of EU-owned firms in the downstream have any spillovers to Romanian suppliers.

Ni, Spatareanu, Manole, Otsuki, and Yamada (2017) examined whether productivity spillovers occurred horizontally or vertically using Vietnamese firm data. They looked at whether the technical spillovers from the foreign-owned plants to the domestically-owned plants occurred horizontally or vertically. Asian MNCs generated positive backward vertical spillovers, however also generated negative horizontal spillovers. There was some evidence of forward spillovers however this was not robust. The Asian MNCs appeared to withhold technology and knowledge from horizontal domestic plants but were willing to be more integrated with their supply chain. In the other ownership groups, EU and US, it was found no spillovers occurred.

Ni, Spatareanu, Manole, Otsuki, and Yamada (2017) found there were greater spillovers from FDI that was ethnically similar. They went on to examine whether Asian MNCs, from ASEAN, generated spillovers. They found that there were few spillovers from these companies, due to the lack of an incentive to source locally. Separating Asian ownership into different groups, Chinese and Taiwanese investment generated positive spillovers, possibly due to institutional similarities between the Vietnamese firms and Chinese and Taiwanese firms, as well as a lower technological gap between them, whereas there were no spillovers from Japanese or Korean firms.

Within the UK, a study examined the effect of FDI of different origins in the UK electronic industry, and identified those plants that were based in Assisted Areas (AAs). Girma and Wakelin (2007) separated ownership into US-owned, Japanese-Owned, and Other and found that Japanese and other FDI had a positive impact upon productivity in domestically-owned plants. This also held for other-owned firms, although not to the same extent. This was not the case however for domestically-owned plants based in the UK AAs. This could possibly be due to a smaller technology gap between investors and the host region, and so a higher absorptive capacity of firms within more developed or advanced regions of the UK, again suggesting that the impact FDI has within a country or region is dependent, in part at least, on the host country or region's characteristics.

This pattern does not hold for the US-owned plants; they found no correlation between US-ownership and the productivity in domestic-owned plants. They suggested that this could be due to the US-owned plants being older and being based in the UK longer. As Harris and Robinson (2003) found in their work, the US advantage diminished over time, as UK-owned plants caught up with the US-owned plants.

Bournakis, Papanastassiou, and Pitelis (2019) also found, after controlling for ownership groups, that MNEs outperformed Domestic Enterprises (DOMEs) in terms of productivity, but only in certain regions, suggesting regional human capital is required to reach a threshold in education and skill levels to achieve this. Overall, MNEs have higher levels of intangible assets (IA) and R&D intensity, when compared with DOMEs and the impact of MNE R&D intensity on regional TFP is greater than that produced by DOMEs. When not controlling for firm characteristics, they found that IA from MNEs had a positive impact on regional TFP, yet when firm characteristics were controlled for, IA's impact was negligible. They separated foreign ownership into four investor groups: EU, USA, Japan and Rest of the World (ROW) and found that R&D (but not AIs) from Japanese and EU MNEs had a stronger impact on regional productivity, whereas only IAs from USA MNEs had a positive impact on regional productivity.

3.4 Spatial spillovers and FDI

The previous section examined the literature regarding the evidence on the performance of FDI across and within countries, sometimes defined as the direct impact of FDI. This section will examine the literature examining the ways in which FDI impacts on domestic plants in terms of spillovers, or indirect impact of FDI.

Spillovers are an indirect impact on a firm from another firm's activities Hymner (1979), and are normally desired due to the presumption that these spillovers have a positive impact on domestic plants. This assumption leads Governments to invest in polices to encourage the formation of clusters to facilitate spillovers. This section will focus mainly on the literature surrounding spatial spillovers, sometimes called agglomeration economies.

3.4.1 Spatial spillover theory

There are two main schools of thought regarding spatial spillovers and the best environments for them to occur; whether spillovers occur intra-industry or whether they occur inter-industry. There is a third additional theory that introduces competition to the intra-industry spillovers, stating its importance to innovation. The three theories are presented below.

MAR Spillovers

Specialisation or intra-industry spillovers, were initially developed by Marshal (1890). He presented three agglomeration mechanisms that gave rise to spillovers: labour market pooling, input sharing, and knowledge spillovers. This suggests firms of the same industry will locate in the same region creating regional monopolies. This facilitates the ease of knowledge transfer between plants, reduces transport costs for both outputs and inputs, as well as giving access to a pool of efficient and trained labour. The nineteenth century industrialisation of the North East of England demonstrates this theory clearly.

Glaeser (1992) built upon Marshal's specialisation spillovers by including the summarised work of Arrow (1962) and Romer (1986) to formulate MAR spillovers. This model assumes that spillovers only occur within the same, or similar, industries. The idea of a monopoly of industries means that there is no transfer of knowledge outside of these industries, only between those that are present in the monopoly (Beaudry & Schiffauerova, 2009). The MAR model also argues that local monopolies are better for innovation than competition (van der Panne, 2004) as plants are able to capitalise on their investment and innovation, internalising externalities, thus increasing economic growth and productivity for that industry. As well as benefiting from the local monopoly, plants also benefit from "collective" economies of scale (Groot et al., 2014). Co-locating enables plants to share common inputs, technologies and a common pool of labour and reduces transport costs. This allows plants to share the fixed costs and to pool risks when it comes to large investments in heavy machinery or the training of workers (Mohanty & Mishra, 2014). An opposing view to the MAR model is one proposed by Jacobs (1970).

Jacobian Spillovers

Jacobs (1970) proposes diversification or inter-industry spillovers and argues that spillovers occur between different, yet complementary industries rather than within the same, or similar, industries. Where different industries are located together, firms are exposed to a diverse range of technologies, which encourages a faster flow of ideas between plants, boosting productivity levels and economic growth. This theory argues that ideas within one industry can be applied to another which encourages the plants to innovate and experiment (Beaudry & Schiffauerova, 2009). Jacobs also states that competition, rather than monopoly, is better for innovation. It encourages plants to innovate, whereas monopolies reduce the incentives and stifle advancements (Jacobs, 1970).

Porter Spillovers

There is a final theory, presented by Porter (1990) in The Competitive Advantage of Nations. He agrees with the MAR model, that spillovers occur within the same industry, especially if the industry in the region or area is highly concentrated, as this stimulates economic growth (Van Stel & Nieuwenhuijsen, 2004). However, like Jacobs (1970), Porter (1990) argues that local competition accelerates innovation and growth rather than local monopolies (Glaeser et al., 1992). This theory accepts that there will be large spillovers between the innovator and other local firms. However, the competition element will force firms to innovate, to prevent falling behind their competitors and drop out of the market (Van Stel & Nieuwenhuijsen, 2004).

Spatial spillovers theory and FDI

The literature defines several channels in which FDI spillovers can occur. Saggi (2002) presents three potential channels for spillovers: Demonstration effects, Labour turnover, and Vertical linkages. Lesher and Miroudot (2008) and Crespo and Fontoura (2007), building upon the work by Görg and Greenaway (2004), present five channels in which FDI spillovers can occur: Skills via labour mobility, Exports and Infrastructure improvements, Imitation, Competition, and Vertical Linkages.

Several of these stem from the spatial spillover theory, MAR spillovers being associated with the channels of Skills via labour mobility, Imitation and Vertical Linkages while the competition channels are associated with Porter spillovers. None of the channels are associated with the Jacobian spillovers, where the spillovers occur in a diverse market or region. This could be due to domestic firms not experiencing spillovers from foreign-owned firms from different industries. It may also be the case that when examining spillovers from foreign-owned firms, researchers have not examined these groups, with the literature focus being on the presence of foreign ownership and its impact on domestic firms within the same, or similar, industries.

3.4.2 Evidence of types of spillovers

All three models agree that geographical location allows spillovers between firms. They all suggest that plants will choose to locate together to maximise the potential benefits of spillovers. However, the evidence regarding these spillovers in the literature is mixed and can depend on how the conditions of the theories are interpreted, especially when it comes to interpreting MAR's condition regarding local monopolies of industries and the stated competition coming from demand for local workers (Glaeser et al., 1992). The papers in section make no distinction between domestic- or foreign-owned firms.

Glaeser, Kallal, Scheinkman and Shleifer (1992) found evidence for both Jacobian and Porter spillovers, but no evidence of MAR spillovers in relation to knowledge spillovers in the US. Van der Panne (2004) found evidence of MAR spillovers which had a positive impact while Jacobian and competition spillovers had a negative impact on regional innovativeness in the Netherlands. Groot et al (2014) also found in the Netherlands, that an increase in regional share increased productivity, while diversity and competition had a negative impact on productivity. Castellani, Driffield, and Lavoratori (2024) found the opposite held when looking at the impact of the presence of MNEs on productivity in the UK manufacturing sector. They found that firms benefited less from FDI when based within highly specialised regions and benefited more when located in more diversified regions. Matlaba, Holmes, McCann, and Poot (2012) looking at the Brazilian Manufacturing industry, found different spillovers present in different regions. In some regions, MAR and Porter's low competition or increased specialisation hold, while Jacobian high competition or diversity held in other regions.

Jofre-Monsent et al (2011) looked at the importance of MAR spillovers in new small manufacturing firms in Spain. Two of the three MAR mechanisms (labour market pooling, and input sharing) impacted on the decision making of new firms, whereas knowledge spillovers had a much smaller impact. Van der Panne (2006) found that MAR and Jacobian spillovers had an impact at different stages of innovation. At the beginning of product development, MAR spillovers were more beneficial, shifting to Jacobian spillovers having a more positive impact on innovators later in development.

Both Martin et al (2011) and Fazio and Matese (2015) looked at the impact of spillovers over time. Martin et al (2011) found that in French plant level data, in the short term, localisation (MAR spillovers) had a small impact on productivity, but their results suggest that in the long term, urbanisation (Jacobian spillovers) was of more importance. Fazio and Maltese (2015) found that over the longer term MAR spillovers had a positive influence, Jacobian spillovers had a negative impact, and Porter's had no significant impact. In the short-term Jacobian and Porter spillovers had large positive impact on productivity, with the MAR spillovers having no impact at all.

3.4.3 FDI and Spillovers

The perception that foreign-owned plants are more productive than domestically-owned plants due to their advantageous characteristics provides an incentive for host countries to encourage foreign firms set up plants within them. There is a hope that the domestic plants will be able to assimilate some of these advantageous characteristics through spillovers through interacting with these foreign-owned plants. However, the empirical evidence supporting this theory is not consistent, suggesting that the presence of FDI alone is not enough to encourage spillovers to domestic plants (Rojec & Knell, 2018).

Li, Chen, and Shapiro (2013) found inter-industry and intra-industry spillovers occurred within China but those findings depended on the level of data aggregation. Intra-industry spillovers (MAR) were found on a national, as well as a subnational level. Those Chinese firms based near cities with foreign innovation from the same industry benefited, but only up to a certain level of concentration of foreign-owned plants. Beyond this threshold, domestic firms experienced crowding out.

Inter-industry (Jacobian) spillovers occurred at a sub-national level, especially within emerging markets. Mitze (2012) examined the differences between outward and inward FDI in relation to spillovers within West Germany, between 1976 and 2008. In the short term, TFP growth was stimulated on a local scale rather than globally. They found that inward and outward FDI stocks drove technical progress, and that inward FDI generated positive and significant productivity spillover effects.

However, in the longer term, outward FDI activity appeared to have a positive spatial spillover effect among Germany's regions, whereas inward FDI and imports could have negative spillover effects. This is possibly due to a substitution effect where inter-regional input-output linkages are scaled back in favour of international ones over the time period.

Keller and Yeaple (2009) examined the international technology spillover from imports and FDI to US manufacturing firms between 1987 to 1996. They found that FDI resulted in large productivity gains in domestic firms and that FDI had contributed to 14% of productivity growth in US firms. These spillovers were mainly absent from low-tech industries, although were quite strong in high tech industries, suggesting that the specific industry characteristics, such as absorptive captivity, played an important role in generating spillovers as found by Al Nasser (2010), Konings (2001), and Borensztein et al. (1998). Nicolini and Resmini (2010) when examining the impact of foreign firms on domestic firms' productivity in Bulgaria, Poland, and Romania found that the existence of spillovers depended upon a firm's absorptive capacity. This was also found in Spanish manufacturing firms by Barrios and Strobl (2002) who stated that only firms with a certain level of absorptive capacity experience positive spillovers from FDI.

The following papers review FDI spillovers in the UK. Driffield (2004) looked at the extent to which foreign-owned manufacturing firms promote productivity growth in domestic manufacturing plants in the UK. They examine forward and backward linkages between foreign-owned and domestically owned plants from the same industry (intra-) or region, different industries (inter-) or different region. They found that the impact on domestic productivity growth is dependent on the nature of the linkages between foreign-owned and domestically-owned firms The gains are greater in those domestic plants which purchase from foreign firms. The authors find this is not the focus of UK regional policy, which focuses rather on backward linkages. They find that while backward linkages maybe beneficial to output and jobs, forward linkages appear to be the mostly likely channel for productivity spillovers.

Harris and Robinson (2004) , however, found that locational and intra-industry spillovers are much less frequent than bulk of the literature suggests. In over a third of industries there was no statistical evidence of intra industry spillovers on domestic plants, and inter-industry spillovers were just as likely to be positive as negative, as some experienced a strong competition effect from the foreign ownership, resulting in a negative impact, as Li, Chen, and Shapiro (2013) found in China.

Haskel, Pereira, and Slaughter (2007) examined whether there were any productivity spillovers from FDI in the UK manufacturing industry between 1973 and 1992. They found a positive significant correlation between domestic TFP and the foreign share of employment in the same industry. They found no correlation between the presence of foreign employment and domestic TFP in the same region.

Girma and Wakelin (2002) found similar results when examining TFP spillovers from foreign firms to domestic firms at a regional level in the UK. They found positive TFP spillovers occur between foreign-owned and domestically-owned firms within in the same region and same industry. However, when foreign-owned firms are in the same industry but sited in different regions there are negative TFP spillovers. There was no evidence of spillovers when FDI was based in the same region but not the same industry.

As in the previous works of Keller and Yeaple (2009), Al Nasser (2010), Konings (2001), and Borensztein et al (1998), regional and industry characteristics were important factors related to the level of spillovers. Regions with a low technology gap between the domestic firms and foreign-owned firms experienced higher and significant spillovers, while domestic firms based in Assisted Area status[11] areas did not benefit from TFP spillovers from foreign-owned firms, perhaps suggesting local firms lacking the absorptive capacity present in more developed regions. They also found, contradicting other work such as Li, Chen, and Shapiro (2013), De Propris and Driffield (2005), and Harris and Robinson (2004), that high levels of competition within a region resulted in that region gaining more from spillovers.

[11] Regions with Assisted Area Status are underdeveloped regions that receive aid, usually through Government schemes, to promote and encourage economic development (Girma and Wakelin. 2002).

Spillovers and FDI channels

The presence of FDI spillovers is not guaranteed within the host country and depends on the characteristics of the host country, the type of spillovers (inter- or intra- industry spillovers) and where these spillovers occur (backward or forward linkages). As Harris and Robinson (2004) found, the presence of spillovers is not as frequent as some of the literature suggests, and this can be due to the way studies have been undertaken. Demena and van Bergeijk (2019) found that spillovers only occur in certain channels, competition being the most important, with the occurrence dependent upon the absorptive capacity of and the technology gap regarding the host country or region, a recurring theme when examining the effect of FDI within host countries.

As FDI spillovers are not always as positive or as widely found within host countries or regions as the theory suggests, some have presented channels in which spillovers can occur in order to understand the truer impact FDI spillovers can have within a host country ((Saggi, 2002) (Lesher & Miroudot, 2008) (Crespo & Fontoura, 2007) (Görg & Greenaway, 2004)). As Javorcik (2004) suggests, the lack of evidence of spillovers may be due to many studies not looking for spillovers in the right place. McGaughey, Raimondos, and la Cour (2020) examined spillovers across 20 EU countries, focusing upon how foreign ownership is categorised: influenced (where foreign ownership accounts for less than 50% of voting shares) and controlled (where foreign ownership accounts for more than 50% of voting shares). They identified different impacts depending upon categorisation: there were positive horizontal spillovers from controlled firms and zero spillovers from non-controlled foreign firms.

Some papers have examined the movement of labour, as a component of MAR spillovers, and considered the importance of a shared labour pool in terms of generating spillovers. Balsvik (2011) examined whether the hiring of workers who have experience and training from MNEs increases the productivity within the non-MNEs within the Norwegian manufacturing industry. After establishing that MNEs have a plant specific advantage over the non-MNEs, they found that workers with MNE experience contributed 20% more to TFP than workers who did not have MNE experience. They also found that workers who moved with MNE experience of more than three years received a 5% wage premium compared with those workers who moved without MNE experience.

Görg and Strobl (2005) examined the movement of workers from foreign to domestic firms within in Ghana's manufacturing sector. They did not find an out-right benefit when previous MNEs workers moved to within non-MNEs. They found that those firms whose entrepreneurs had worked in multinationals within the same industry were more productive than other domestic firms. However, there is no evidence regarding the impact of the movement of previous MNE workers moving to firms based within different industries, suggesting that the knowledge gained by the entrepreneur is only beneficial when it is within the same industry. They also found that where the entrepreneur received training only from the multinational, this had no effect on productivity.

The importance of labour mobility in the transfer of knowledge is an important channel for FDI spillovers which is often overlooked in the literature. A possible reason for this is that the channel is difficult to establish, as it requires the tracking of individual workers across the economy and the ability to identify those who have worked in MNEs, and in many cases this data does not exist (Saggi, 2002). Many countries lack the data sets to perform such studies.

Greenaway, Sousa, and Wakelin (2004) examined export spillovers in regard to domestic firms in the UK manufacturing industry between 1992 and 1996. The level of foreign production in the sector had a strong, positive influence on the probability of UK-owned firms deciding to export. It was also positively influenced by intensity of R&D expenditure, the relative importance of MNE production, and MNEs export activity in the host market. When examining export propensity, MNEs had a positive impact. Domestic firms were positively affected by the intensity of R&D expenditure and the relative importance of MNE production. However, they found no significant evidence of externalities (spillovers) due to export activity. Again, the presence of foreign production, therefore competition, within the sector was the most important channel.

Imitation spillovers are the classic transferal of ideas, products, and processes between foreign-owned plants and domestic-owned plants (Görg & Greenaway, 2001). Such imitation can be achieved through working with foreign-owned plants through supply chains, sharing the labour pools, or as a result of reverse engineering (Das, 1987).

Y. A. Zhang, Li, and Li (2014) considered the Chinese manufacturing industry, and found that the overall effect on productivity of the presence of foreign-owned firms entering an industry on domestic plants was positive, but diminished over time. Harris and Robinson (2003) also found that the advantage possessed by foreign-owned plants, mainly US, declined over time, possibly due to the UK-owned plants being able to assimilate the advantage the US firms possessed.

Zhang et al (2014) test whether imitability is a vital for spillovers to occur. They found that the positive relationship was stronger when foreign-owned plants have lower export intensity, and lower intangible asset intensity, both being attributes linked with low barriers to imitation. They conclude that the lower the barriers to imitation, the greater the effect of FDI spillovers over time. Brambilla, Hale, and Long (2009) also used the Chinese manufacturing sector when they examined whether the FDI encouraged imitation or innovation. They found that a higher proportion of foreign-owned plants in an industry was associated with new product introduction in domestic plants. This was more likely to occur in less-sophisticated firms[12], supporting their model that firms are more likely to imitate rather than innovate.

FDI can increase and encourage competition within industries or regions and some studies suggest that such competition is a vital channel for spillovers to occur (Demena & van Bergeijk, 2019). The introduction of foreign-owned affiliates can provide an incentive for domestic firms to innovate and for technology diffusion to occur (Harrison, 1994).

Markusen and Venables (1999) developed a framework that examined the impact competition from FDI can have on local industry. They suggested two channels where FDI can have an impact: through competition effects in the product and factor markets which can reduce the profits for local firms, or through linkage effects to supplier industries which would reduce the input costs and raise profits. They found that the addition of FDI within the host economy results in welfare improvements. They also suggested that the addition of FDI can act as catalyst for domestic firms to develop, to the extent that the domestic firms can out compete the multinationals within the industry.

While the additional of foreign firms can encourage domestic plants to adapt and innovate, it can also result in domestic firms being crowded out of the market by the foreign-owned plants (Aitken & Harrison, 1999). As a number of previous studies have suggested, competition can result in negative spillovers especially in the short term. Girma et al (2015) and Reis (2001) theorise that domestic plants are not able to compete with foreign-owned plants due to the advantageous characteristics or assets of these foreign-owned firm. Reis (2001) in particular disagrees with Markusen and Venables (1999) in regards to the impact on welfare, finding that within R&D sectors, foreign-owned firms could simply transfer knowledge back to their home country, and where this is the case it results in reducing welfare within the host country.

Javorcik (2004), in her paper examining the presence of spillovers in Lithuania, argues that the lack of spillovers found in previous studies is due to these studies looking for spillovers in the wrong places. Foreign-owned firms would attempt to prevent positive spillovers because these would benefit their local competitors. She suggests these firms are more likely to share knowledge vertically, along the supply chain, enabling them to have access to the inputs they require within the host country, with minimal risk of benefitting local competitors. In her analysis of firm-level data in Lithuania, she found positive and significant relationship between FDI and backward linkages, but a negative relationship

[12] These are defined for medium size, small market share, non-exports, low-capital intensity, less-educated, no imported equipment, and no certified products.

with forward linkages. This is also found by Ha, Holmes, and Hassan (2023) when examining spillovers in Vietnam, showing a negative impact on productivity through forward linkages and positive spillover though backward linkages. This could be a result of foreign firms selling more advanced components at a higher price to domestic firms further down the supply chain. Where this takes place, the domestic plants have increased input costs. She found the positive effect only occurred in firms that were jointly owned with a domestic firm, as these firms were more likely to source from local suppliers. This is echoed in Aitken and Harrison (2003) who found that productivity was greater in those firms which were jointly owned with a domestic firm. Iršová and Havránek (2013), when performing a meta-analysis, concluded that the average effect of horizontal spillovers is zero, although this conclusion depended on the estimation specification, as well as the host country's and foreign investor's characteristics.

Barrios, Görg, and Strobl (2011) agreed that the presence of spillovers was dependent on the model specification used, when examining vertical linkages in Ireland. Certain model specifications influenced whether backward spillovers were positive or negative. They also found a negative relationship between technology gap, trade openness, patent rights and being fully owned, and horizontal spillovers. This had also been found by Aitken and Harrison (2003) and Javorcik (2004). There was a positive relationship within the service sector between the determinants of human capital and the service sector performance, potentially because of sharing a similar labour pool, one characteristic of MAR spillovers.

Blalock and Gertler (2008) studied the Indonesian manufacturing industry and agreed with Javorcik (2004), finding evidence of vertical spillovers where the foreign-owned entrant purchases from domestic suppliers. Domestic firms experienced productivity gains, greater competition, and lower prices amongst local firms. However, there was very little evidence of horizontal spillovers, suggesting the knowledge transfer did not take place between competitors. Crespo, Fontoura, and Proença (2009), like Blalock and Gertler (2008), found evidence of positive backwards spillovers when foreign firms purchased from domestic firms. They found evidence of negative horizontal spillovers, potentially due to competition within the Portuguese manufacturing industry.

There is some evidence of horizontal spillovers within the literature. Unlike Javorcik (2004), Sari, Khalifah and Suyanto (2016) found that horizontal spillovers from foreign firms had a positive impact on productivity and efficiency in domestic manufacturing firms in Indonesia. The impact of vertical spillovers was mixed, backwards spillovers had a positive impact on efficiency within domestic firms, but a negative impact on productivity. Forwards spillovers had the opposite impact, a positive impact on productivity but a negative impact on efficiency. Overall, they found that an increasing presence of foreign ownership had a negative relationship with productivity in domestically-owned firms, but a positive impact upon efficiency. Bournakis (2021) suggests that the failure to find any evidence of horizontal spillovers from those papers was due to the researchers not taking into account the geographical proximity of foreign-owned plants. The failure to find vertical spillovers was suggested to be a result of previous research not acknowledging the role of direct ties or product differentiation between domestic-owned firms and foreign-owned firms. Using data from six EU countries (France, Germany, Hungary, Italy, Spain, and the UK) and taking these new aspects into account, Bournakis found evidence of all three (Horizontal, Backwards, and Vertical) types of spillovers which had a positive impact on TFP within domestic firms.

In the UK manufacturing industry, Girma, Görg, and Pisu (2008) examined productivity spillovers from FDI, horizontally, backwards and forwards. They found that the impact of the FDI differed dependant on whether the domestic firm was an exporter. Unlike Javorcik (2004), they found evidence of horizontal spillovers between MNCs and exporting domestic firms, but not between MNCs and non-exporting domestic firms. They found that both exporters and non-exporters experienced backwards spillovers from domestic market orientated FDI, which increased with the domestic firms' absorptive capabilities. This is in line with the research done by Javorcik (2004). However, the impact of export oriented FDI through backwards linkages had a negative impact on the domestic supplier's productivity, possibly due to export orientated FDI not creating connections with local suppliers, or local suppliers not being able to provide the required inputs. They also found no significant evidence of forward linkages, as in the work by Javorcik (2004).

Görg and Hijzen (2004) also found evidence of intra-industry, or horizontal spillovers, due to the presence of foreign-owned firms in the UK. Spillovers were dependent on the characteristics of both the domestically-owned and the foreign-owned firms. Domestic firms which exported benefited more from productivity spillovers from foreign-owned firms, but only where these foreign-owned firms were export oriented. Those domestic market oriented foreign-owned firms tended to have a negative impact due to the tendency to crowd out the domestically-owned plants. Those domestic plants that did not export did not benefit from any presence of foreign-owned firms.

3.5 Conclusion

Theory would suggest that foreign-owned plants have a productivity advantage over domestically-owned plants. The foreign-owned plants require the advantageous characteristics outlined earlier in this thesis, more advanced technology, better capital, and superior management and production systems, to enable them to compete successfully with the already established domestic firms and recoup set up costs.

However, in the empirical literature, these advantages are not as evident as the theory would suggest. There are studies which find foreign ownership has an advantage over domestic plants. Lee (2007), Gopinath et al (2003), Khawar (2003), and Girma et al (2015) in their studies found that foreign- owned plants had an outright advantage over the domestically-owned plants. However, other studies, when controlling for host country characteristics, industry type, and ownership group found the outright advantages foreign-owned plants were deemed to possess do not hold. Bitzer et al (2005) found the positive impact of FDI across 17 countries is not consistent. Fu (2008) and Borensztein et al (1998) found the location of FDI within their study areas of China, influenced the FDI impact on host regions. Konings (2001) and Hayakawa et al (2013) found the host country characteristics had an impact on the effect of FDI.

There are studies which examined the claim that foreign firms self-select into the more productive industries, giving the appearance that foreign firms were more productive, when in fact they had simply chosen to base themselves within more productive industries. Benfratello and Sembenelli (2006) found this in examining the Italian manufacturing sector, and it was also seen by Salis (2008) in manufacturing plants in Slovenia. Guadalupe et al (2012), Schiffbauer et al (2017), and Arnold and Javorcik (2009) found that despite foreign firms self-selecting these more productive industries, they were still more productive after acquisition when compared with domestic plants within those industries.

The literature also found that the ownership group of foreign-owned firms had an impact on productivity. Globerman, et al (1994), and Doms and Jensen (1998) both found that ownership group impacted upon the productivity of the manufacturing plants. Aitken and Harrison (1999) found the most productive plants were those that were jointly owned by a domestic firm and a foreign firm. Harris (2002) found that not only ownership, but also industry type has an impact on productivity within foreign-owned plants. Despite the advantages foreign-owned plants possess, depending on the industry type in which they were based, there were instances where some foreign-owned plants performed worse than the domestically-owned plants in the same industry, potentially as they seek to assimilate technological advances or similar benefits from domestically-owned firms.

The impact of the presence of foreign-owned plants is seen to be influenced by host countries' characteristics, and the ownership group of foreign-owned firm. Zhang et al (2010) found that a high diversity of FDI benefited the domestic firms the most. FDI can have a negative impact; Azeroual (2016) found French investment had a negative impact in the manufacturing industry in Morocco. This potentially stemmed from the motivation of the FDI. Some foreign-owned firms may choose to not engage with domestic plants, who do not then benefit from spillovers and may be crowded out of the market by the foreign-owned plants.

These findings make it difficult to draw an overall conclusion that FDI benefits the host country as there are many different factors which influence the impact FDI has in a host country. Ownership group, industry type, along with host country characteristics, such as wage levels, and technology gaps are important factors that need to be considered when examining how FDI can impact upon a host country or region.

Regarding the impact of FDI within the UK, there is a significant lack of literature examining the regional impact of foreign ownership, in that most studies of the UK have examined the impact of FDI at a national level. Where any regional analysis has been undertaken, it has not covered the North East region of England or its specific regional host characteristics. It has similarly failed to capture differing regional host characteristics shown across UK regions. Such regional host characteristics are identified within the existing literature as important in influencing the impacts of FDI, and how it performs in the creation of positive spillovers within a host region. This thesis addresses these gaps in the current knowledge base.

In recent years, there has been a shift in the literature on a micro-level to examine more of the indirect impacts of FDI, such as spillovers to local and domestically-owned plants, rather than the overall impact of foreign ownership on plants within a host country. This is presumably to help guide policy makers when proposing strategies around FDI.

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4. Data and Methods

4.1 Introduction

This chapter presents the data which underpins this thesis and the way in which the datasets used have been constructed. This chapter will also cover the estimation method used to perform the analysis in subsequent chapters. The data being used in the subsequent chapters is taken from the Annual Respondents Database (ARD) and Annual Business Survey (ABS), both of which are compiled by the Office of National Statistics (ONS). The key variables being used are Capital Stock, Employment, Intermediate and Ownership dummy variables created from the data. The data used runs from 1984 to 2014 so capturing the introduction of the EU single Market and preventing the data being influenced by the Brexit discussion and subsequent referendum. To overcome endogeneity problems, System GMM will be used to estimate the model.

4.2 Business Registers

The ONS surveys form the ARD and the ABS as outlined above. These are sampled from the current ONS business registers. These registers hold information on businesses that account for nearly 99% of the UK economic activity. The ARD, prior to it being discontinued in 2008, was comprised of the data from two registers. The first was the CSO business register (known previously as the Business Statistics Office [BSO] Business Register) which was used until 1993. From 1994 onwards the Inter Departmental Business Register (IDBR) was used for ARD (until 2008) and is currently used for the ABS which has replaced it (2009 onwards).

4.2.1 CSO Business Register

The CSO business register was used to compile the ARD until 1993, its main statistical unit being the 'establishment'. Establishments are comprised of one or more local units, each local unit consisting of individual sites or factories that are owned by the establishment. There are three main units in the CSO Business Register (in descending aggregation):

- Enterprise group - the group of all legal units under common control
- Establishment - the smallest group of legal units which could provide the full range of data required for the survey
- Local unit - the individual site or workplace where the enterprises' activity, such as manufacturing and processing, takes place

When there is more than one local unit as part of an enterprise group, these units are termed 'multiple' establishment firms, while those establishments that are reporting on themselves alone, and have no dependent local units reporting to them, are termed 'single' establishments. Establishments which have multiple local units reporting to them are termed 'parents', with the local unit being named 'children'.

This system changed in 1987, with the introduction of company reporting, in line with the European Communities' Directives. On paper, this meant that companies replaced establishments as the unit for the surveys. However, to ensure continuity within the register, those large mixed-activity and/or those geographically spread companies continued to be split by activity and/or region. This became known as the 'reporting unit'.

There were several issues with this register. Firstly, it did not contain any up-to-date employment records, as VAT records were the main source of information. The use of VAT records was introduced in 1984, as previously the register was compiled from numerous sources which made it difficult to ensure completeness and to prevent duplication. Because the VAT records do not provide information regarding employment this was imputed from the VAT turnover. This results in much of the employment data being old, and for some units there has been no update to their employment data. A further issue is that the register had a cut-off point of 20 employees, meaning that there was a lot of what was described as 'deadwood' at the lower end of register.

4.2.2 Inter Departmental Business Register

After 1994, the register used to compile ARD was changed to the Inter Departmental Business Register (IDBR). This included records from the VAT register and the PAYE register, with the aim of improving coverage and of improving the coherence of estimates (such as wage costs and productivity) produced from the surveys. This register covers all UK businesses registered for VAT or PAYE (excluding the Channel Islands and the Isle of Man). There are some legislative differences between Great Britain (England, Scotland and Wales), and Northern Island. The ONS is responsible for the IDBR within Great Britain, while the Department of Enterprise, Trade and Investment Northern Ireland (DETINI) is responsible for the Northern Irish part. This results in some differences between the two parts. It should also be noted that the ONS runs the Annual Register Inquiry annually, while DETINI runs a two-yearly Census of Employment.

The reporting units for the IDBR can be classified into three groups: Administrative, Statistical, and Reporting. The Administrative units are the VAT traders and the PAYE employers. The statistical units can be spilt into four units defined using the EU regulation on Statistical Units (EEC 696/93): Enterprise[13], enterprise group[14], local unit[15], and kind of activity unit (KAU)[16].

The reporting unit which relays the business survey data to the ONS is generally the same as the enterprise, but it can be divided into local units that correspond to the KAU, for example when the enterprise is a mixed-activity company.

The IDBR is updated using the Annual Register Inquiry, alongside the administrative sources. This, alongside the Annual Business Inquiry, is designed to provide statistics for small geographical areas. These are used to ensure that the IDBR remains accurate by annually checking the existence of enterprises (ARI/1) and confirming the details of larger, new, administrative units on a quarterly basis (ARI/2). This is carried out on businesses based in Great Britain, as DETINI carries out continuous proving for Northern Ireland based enterprises.

Reporting units

The reporting unit is the business unit that is sent the questionnaire by the ONS. The reporting unit can represent a whole enterprise, or parts of an enterprise made up of local units. Generally, the reporting unit is the enterprise, although there are occasions where the enterprise unit is separated

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[13] 'The enterprise is the smallest combination of legal units that is an organizational unit producing goods or services, which benefits from a certain degree of autonomy in decision-making, especially for the allocation of its current resources. An enterprise carries out one or more activities at one or more locations. An enterprise may be a sole legal unit.' ONS. (2006). Business Structure Database User Guide. In S. a. E. M. A. a. R. Division (Ed.), (Vol. 1). Newport: Office for National Statistics.

[14] 'An enterprise group is an association of enterprises bound together by legal and/or financial links. A group of enterprises can have more than one decision-making centre, especially for policy on production, sales and profits. It may centralize certain aspects of financial management and taxation. It constitutes an economic entity which is empowered to make choices, particularly concerning the units which it comprises.' Ibid.

[15] 'The local unit is an enterprise or part thereof (e.g. a workshop, factory, warehouse, office, mine or depot) situated in a geographically identified place. At or from this place economic activity is carried out for which – save for certain exceptions – one or more persons work (even if only parttime) for one and the same enterprise.' Ibid.

[16] 'The kind of activity unit (KAU) groups all the parts of an enterprise contributing to the performance of an activity at class level (four digits) of NACE Rev 1 and corresponds to one or more operational subdivisions of the enterprise. The enterprise's information system must be capable of indicating or calculating for each KAU at least the value of production, intermediate consumption, manpower costs, the operating surplus and employment and gross fixed capital formation.' Hellebrandt, T., & Davies, R. (2008). Some issues with enterprise-level industry classification: Insights from the Business Structure Database. *Virtual Micro Data Laboratory Data Brief*, *5*.

into different local units, based either upon size, or economic activity. These local units will then become the reporting unit. Figure 4-1 shows the relationship between the different unit types.

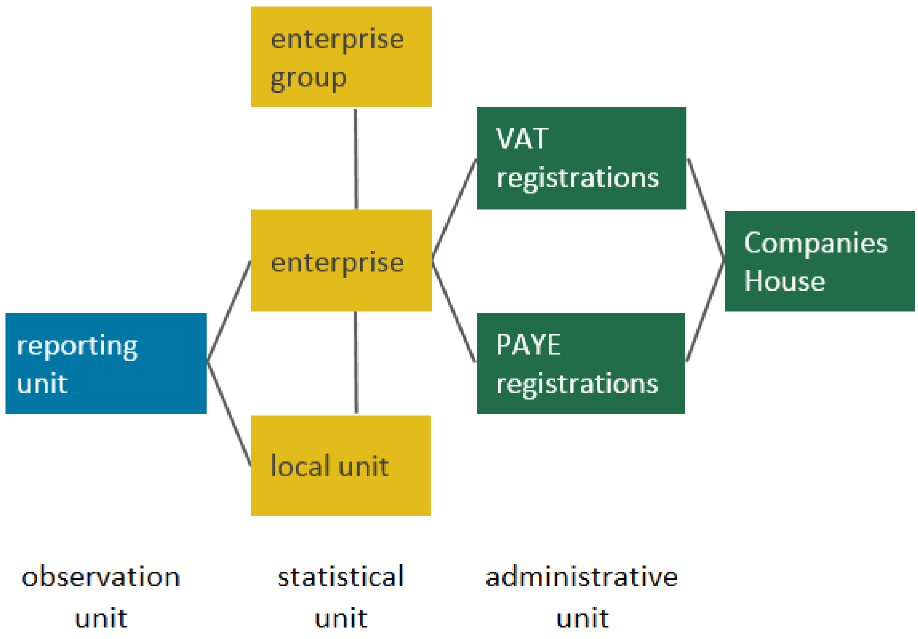

Figure 4-1 Relationship between the different units and groups Source: Office of National Statistics

Each local unit is assigned a single SIC code, related to the principal activity. This is the activity in which most people are employed. While the unit may carry out other economic activities, the focus is on that which employs the most people in any given unit. Businesses can be reclassified into different SIC groups. This may occur even when there are slight changes to the unit's operation.

4.3 Annual Respondents Database

The Annual Respondents Database (ARD) is a census of large businesses and a sample of smaller ones which ran from 1973 up until 2008. It was compiled from annual surveys produced and administered by the Office of National Statistics. The results from these surveys are used to create micro-data which allows individual reporting units to be followed through time. The data collected for the ARD is confidential and only those approved by the ONS can access this data.

The ARD stored the data collected by the ONS from two annual surveys: the Annual Census of Production and the Annual Census of Construction. These two surveys cover almost all production and construction[17], and from 1998 the Annual Business Inquiry (ABI) was also included. This meant that an additional six surveys were included, covering distribution and other service activities. Therefore from

[17] Construction was only included after 1992.

1998 onwards service industries were included in ARD. The inclusion of the ABI meant that the coverage of ARD was increased from 15,000 firms in 1980 to over 70,000 in 1999.

The Annual Census of Production (ACOP) was an annual survey which covered only production industries; it also asked for the year-average of employment from respondents. It ran between 1970 and 1997 before it was replaced by the Annual Business Inquiry in 1998. The Annual Census of Construction (ACOC) was introduced in 1992 and covered the construction industry and collected data from respondents on the year-average employment. This was also replaced by the Annual Business Inquiry in 1998.

The Annual Business Inquiry was the forerunner of the Annual Business Survey, introduced in 1998. It was an annual survey across the whole market economy[18] with the exception of financial services. This survey was comprised of two parts: the first part covering employment, and the second part covering financial data.

4.4 Annual Business Survey

In 2008, the ARD was replaced by the Annual Business Survey. The ABS was formally known as the Annual Business Survey-part 2 (ABI/2), and was an annual survey of businesses covering about two-thirds of the UK economy in terms of GVA.

The ABS questionnaires are distributed to almost 62,000 businesses in Great Britain by the ONS, while in Northern Ireland around 11,000 businesses are surveyed by the Northern Ireland Statistical and Research Agency (NISRA). This is the largest survey conducted by the ONS both in terms of the number of respondents and in the number of questions asked (near 600). It provides high level indicators of economic activity and is a large contributor of business information to the UK National Accounts.

The ABS covers more than production and construction. Using the 2007 SIC industries, the ABS covers part of section A (Agriculture-support activities, forestry, and fishing), sections B to E (production industries), section F (construction industries), section G (distribution industries), and sections H to S[19] (Other service industries). There are some industries that are not included, such as crop and animal production, financial activities, section O (public administration and defence), Section T (activities of

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[18] The ABI covers two thirds of the UK economy. It initially covered production, construction, motor trades, wholesale retailing, catering and allied trades, and property services. In 2000, partial agriculture, hunting, forestry and fishing.

[19] With only Insurance and reinsurance (65.1 and 65.2) included in section K, excluding public services in section P, and excluding public sector and medical and dental practice activities in section

households as employers; undifferentiated goods and services-producing activities of households for own use), and Section U (activities of extraterritorial organisations and bodies).

Selected Samples

The businesses chosen to take part by the ONS are selected using the stratified sample design outlined above. Reporting units are grouped into 'cells', based upon three strata: plant employment size[20], Standard Industrial Classification (SIC)[21], and geographical region[22]. For the ABS, there are approximately 4,800 cells. The size of the sample in each cell is determined by an algorithm, which produces a sample across all cells with the lowest estimated variance. This is deemed more accurate and efficient than a simple, unstratified random sample.

The selected businesses are given a unique number, so that they can be identified within the cell and the survey. Generally, the sample is selected for two years, with a year-to-year overlap with the next selected group, i.e. in any given year, half of the sample will be newly selected, and half will be the selected sample from the previous year. If a selected unit moves into a different cell, they can be selected for a second two-year period. Where there is a cell with a low unit count, then the likelihood of being selected for consecutive periods increases. This is also the case where there are cells within the largest and smallest size bands.

All enterprises within the largest bands are selected every year, because there are fewer of them, and they employ a large number of workers. Those businesses in the smallest bands are only selected for one year, instead of the two, and will not be reselected for the next three years. 4.4.1 Variables in the data

There are a number of variables that are available for researchers and government departments within

the data. The list of variables and definitions can be found in Table 4-1 Variable descriptions

below.

Key Variable	Definition
Ln Lagged Output (y_{it-1})	*Ln* real gross output
Ln Capital (k_{it})	*Ln* plant and machinery capital stock
Ln Employment (l_{it})	*Ln* numbers employed in plant

[20] There are six employment bands: 0 to 9, 10 to 19, 20 to 49, 50 to 99, 100 to 249, and 250 or more. In the case of industries which have high employment and low turnover there are additional bands of 100-999 and 1,000 or more.

[21] For England and Wales four digit SIC codes are used, while for Scotland two-digit SIC codes are used.

[22] The regions used are England and Wales, and Scotland.

ln Intermediates (n_{it})	*Ln* intermediate inputs
Foreign (FO) effects (FO_{it})	Dummy variable coded 1 if plant is owned by a Non-UK company
EU-Owned	Dummy variable coded 1 if plant is owned by an EU company
ROW-Owned	Dummy variable coded 1 if plant is owned by an ROW company
US-Owned	Dummy variable coded 1 if plant is owned by an US company
Year	Year dummies
Age	Number of years since opening
Multi SIC	Dummy coded 1 if enterprise has more than one 4-digit SIC80 across plants owned
Multi Region	Dummy coded 1 if plant belongs to an enterprise operating in more than on UK region
Single Plant	Dummy coded 1 if plant comprises a single-plant enterprise
Herfindahl Index	Herfindahl index of industry concertation
Newcastle	Dummy variable coded 1 if the plant is within the Newcastle local authorities
Sunderland	Dummy variable coded 1 if the plant is within the Sunderland local authorities
Teesside	Dummy variable coded 1 if the plant is within the Teesside local authorities

Table 4-1 Variable descriptions

The data runs from 1973 to 2014, with variables being collected from 1970, and this thesis uses a sub sample between 1984 to 2014. This period was selected to cover announcement of the EU single market in 1986, the entry into the EU single market in 1993, and closes before the Brexit Referendum legislation was brought forward in 2015, meaning that the data is not influenced by this discussion. It covers sufficient time periods to enable use of the System GMM method as outlined in the following section. The intermediate inputs are raw materials, and other inputs which are used up in production of goods.

There are a number of dummy variables which are used as descriptors of the plants and which may also have an impact on the plant's output or productivity. These variables are coded 1 if the plant meets the requirement for the chosen variable, and 0 if the plant does not.

Some plants are single plant enterprises, so differing from enterprises which are made up of multiple plants. These "Single Plant" enterprises are coded as such in the data. Other enterprises have plants based in multiple UK regions, and this has also been identified and coded in the data. Enterprises with plants in multiple different 1980 SIC industries, are similarly identified and coded within the data.

The Herfindahl index (1950) is a measure of concentration of industries and is calculated by the sum of the squared market shares of firms, and is used as a tool for assessing the intensity of competition (Spiegel, 2021).

The age of the plant is obtained from the date when the plant was first observed on either ARD/ABS or on the Business Structure Database (BSD) in the ONS. This is more accurate than using the date when they were first included in the survey, as some industries (such as construction and services) were not added to ARD until the 1990s.

The BSD compiles information from a number of different surveys (mainly from the service sector) dating back to the 1970s and 1980s and its use provides information for the date these plants were first included in these surveys.

Regarding ownership groups, the different groups of ownership are identified in the data, making it possible to create different variables based upon ownership. Using this facility, for this thesis four ownership sub-groups were created, all of which are coded 1 when a plant is identified as falling within one of the following sub-groups: foreign-owned, EU-owned, US-owned, and ROW-owned.

The industrial areas variables, Newcastle, Sunderland, and Teesside are coded as dummy variables based upon the Local Authority areas which make up those areas. These are used to examine whether there is an impact on a plants' productivity through being based in those industrial areas.

Calculation of Capital Stock

I have utilised the capital stock variable within the data set, defined in this case as plant and machinery, which was calculated by Harris and Drinkwater (2000) using the Perpetual Inventory Method (PIM) and plant level estimates of real investment. They used this to develop a method to construct capital stock estimates. Their work also included efficiency losses because of capital deterioration through obsolescence and depreciation.

The PIM is a method that depreciates the capital value and adds the net investment for the following years, and continues this for all future years. A difficulty is establishing the initial year's level of capital stock. This is done by calculating the total industry capital which is then shared between plants. By using a ratio of plant investment (the sum of individual plants investment) to industry investment, this corresponds to the individual firm's share of capital. Harris and Drinkwater (2000) devised a method using variables that are related to capital stock which are available for all years[23]. Harris and Drinkwater (2000) suggest there are three methods for the allocation of capital stock: to use total purchases, to include an employment weighting, or to use employment and weight this with total purchases. The method which produced the best results was that using only total purchases. Firms are

[23] This initially was either total purchases or materials and fuels. From 1997 onwards there was additional variables available: Number of local units, Spending on insurance, or spending on road transport.

now allocated a share of capital stock when they first enter the dataset. Additionally, price deflators, constructed by SIC letter and asset type, are required to ensure any price changes in the asset value are adjusted over time.

When the base year's capital stock has been established the PIM can be run. The depreciation rates that are set out by the ONS are used: Plant and Machinery 6%, Buildings 2%, and Vehicles 20%. Harris (2005) used the Denison (1972) approach of weighting the gross and net stock figures in a ratio three to one in order to obtain the net stock figures needed to get the wanted pattern of deterioration. This method is preferred to a geometric approach, as the geometric approach assumed a much higher, and economically unreasonable, rate of deterioration.

$$Firm\ Capital\ Stock_{assest,year_i} = (Allocation\ firm\ Capital_{assest} * \ Firm\ Investment\ Share_{asset}) + rncapex_{year_i}$$

$$Firm\ Capital\ Stock_{assest,year_{i+1}} = \left[Firm\ Capital\ Stock_{assest,year_i} * (1 - assest\ depreciation)\right] + rncapex_{year_{i+1}}$$

$$Firm\ Total\ Capital\ Stock_{year} = \Sigma Firm\ Capital_{asset}$$

Equation 4-1 Perpetual Inventory Model used to calculate capital stock

There is a risk that some of the capital stock values will be negative, which is not possible. To overcome this, an additional injection of capital at a plant level is made, over a series of years near to the year when the plant's capital stock turns negative. When the investment figures are increased in the proceeding years, the PIM is re-run.

A benchmark estimate of manufacturing capital stock is calculated for each industry from 1948 to 1969 using 3-digit industries. This is then allocated to each plant in that industry, in the year following the benchmark year. Failure to include the capital scrapping due to plant closures inflates the capital stock, as it is not being accounted for in the aggregate. When the capital scrapping was not accounted for in this way over time, the uncontrolled capital stock was inflated over the time period, so by 1993 capital stock was nearly 44% higher.

4.5 Data Descriptors

Table 4-2 below contains the means and standard deviations for the variables used in this analysis for plants in the whole of the UK, plants within the North East, plants within the South East, and plants based in the North of England. Compared to the national average, both the North and North East have a higher average output, whereas the plants in the South East have a lower average output. This is the same regarding the level of employment and intermediates inputs. Plants in the North of England were on average older than the national average, whereas plants in the South East and North East were on average younger.

On average, there are fewer single plant enterprises in the North East and North of England, with more in the South East. There are, on average, more North East, South East and North of England based plants that are in Multi SIC enterprises compared with the national average. This is the same for Multi-Region based plants. The average for the Herfindahl index is similar across each region and similar to the national average. There are, on average, more foreign-owned plants in the North East of England and the South East of England when compared with the national average, whereas there are fewer in the North of England.

	UK		North East		South East		North	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Ln Gross Output	0.833	1.917	0.882	1.996	0.769	1.909	0.912	1.951
Ln Capital	-0.976	3.336	-0.826	3.161	-1.113	3.387	-0.820	3.289
Ln Employment	3.481	1.671	3.573	1.759	3.351	1.676	3.590	1.678
Ln Intermediates	0.205	2.031	0.265	2.101	0.125	2.007	0.291	2.070
Ln Age	1.973	1.044	1.964	1.045	1.908	1.045	2.008	1.040
Single	0.273	0.446	0.221	0.415	0.278	0.448	0.260	0.438
Multi SIC	0.483	0.500	0.517	0.500	0.485	0.500	0.494	0.500
Multi Region	0.580	0.494	0.633	0.482	0.589	0.492	0.589	0.492
Herfindahl	0.099	0.100	0.103	0.103	0.095	0.099	0.102	0.104
FO	0.166	0.372	0.204	0.403	0.187	0.390	0.162	0.369

Table 4-2 Means and Standard Deviations of variables

4.3.1 Regional differences between ownership groups

The following tables compare the differences in means within ownership groups at a national level, for the North East, South East and the North of England. Table 4-3 below presents the means of each ownership group at a national level. Foreign-owned plants have a greater average output, a greater level of capital, and higher employment than the UK-owned plants. Foreign-owned plants are, on average, also older than the UK-owned plants. There are, on average, more UK-owned single plant enterprises compared with foreign-owned plants, with more foreign-owned plants being a part of Multi-SIC and Multi-region enterprises compared to UK-owned plants. Foreign-owned plants appear to have more market power than UK-owned plants.

National	UK-owned		FO	
	Mean	SD	Mean	SD
Ln Gross Output	0.647	1.866	1.760	1.900
Ln Capital	-1.178	3.381	0.018	2.904
Ln Employment	3.393	1.634	3.921	1.777
Ln Intermediates	-0.004	1.983	1.246	1.949
Ln Age	1.946	1.038	2.108	1.061
Single	0.301	0.459	0.133	0.339
Multi SIC	0.464	0.499	0.574	0.494
Multi Region	0.537	0.499	0.798	0.401
Herfindahl	0.095	0.098	0.115	0.106

Table 4-3 Mean difference between ownership groups for the UK

North East

In the North East, as seen with the national average, foreign-owned plants have a greater average output, greater level of capital, higher employment, and greater intermediates. On average, there are more UK-owned single plant enterprises when compare with foreign-owned plants, while there are more foreign-owned plants based within Multi-region and Multi-SIC enterprises. The North East and the national picture are similar in terms of the level of competition. This is shown by the similar Herfindahl Index averages.

North East	UK-Owned		FO	
	Mean	SD	Mean	SD
Ln Gross Output	0.67	1.95	1.76	1.97
Ln Capital	-1.09	3.20	0.27	2.71
Ln Employment	3.48	1.72	3.98	1.85
Ln Intermediates	0.03	2.04	1.24	2.05
Ln Age	1.91	1.04	2.18	1.03
Single	0.24	0.43	0.14	0.35
Multi SIC	0.50	0.50	0.59	0.49
Multi Region	0.59	0.49	0.80	0.40
Herfindahl	0.10	0.10	0.12	0.11

Table 4-4 Mean difference between ownership groups for the North East

4.6 Methods of Estimation

Total factor productivity (TFP) can be estimated using a variety of techniques; both non-parametric and parametric methodologies can be used. Both methodologies have benefits, from simple configurations to overcoming endogeneity within variables. However, both have weaknesses, such as being significantly impacted by measurement errors and sacrificing precision for flexibility. A more detailed discussion in the differences between parametric and non-parametric methods is given in Appendix A.2.

The parametric estimation technique which will be used in this thesis is the System GMM. Blundell and Bond (1998), developed the Generalised Method of Moments (GMM) which is a standard first-differenced estimator that can be used to estimate dynamic error component models. The standard GMM estimation method requires the data to be first differenced, to remove the fixed effects. These first differences would then be estimated (Roodman, 2009). There are issues with this method. If there are fixed effects persisting, then the differenced GMM becomes biased and imprecise due to the instruments being weak. The variables then become less reliable and informative due to the number of times the data has to be differenced to remove the fixed effects.

A solution is to use System GMM, which estimates in both differences and levels equations simultaneously (Roodman, 2009). The model has better finite sample properties, is flexible when generating instruments, and remains a good predictor of variables even if they are very persistent, as well as overcoming the presence of endogenous variables (Blundell & Bond, 1998). However, due to two equations being estimated simultaneously, the number of instruments can increase rapidly relative to the sample size. This can result in the over-fit of endogenous variables, biasing coefficients towards the non-instrumented estimators (Roodman, 2009). This model requires several time periods, and it can risk the coefficients being underestimated, especially if instruments are weak.

As parametric methods perform better with data over time periods and are better at providing estimates for factor inputs and statistical findings, a parametric method will be used. As some of the variables that are used in the estimations are endogenous, a method is needed to overcome this. System GMM is a parametric method which overcomes endogenous variables, remains a good predictor even with very persistent variables, and has better finite properties when compared with the original GMM method.

System GMM has some limitations, such as many instruments resulting in the over-fitting of endogenous variables, biasing the coefficients, which needs to be taken into account when running the estimations. This method also needs several time periods to be able to perform consistently. The data being used in this thesis runs from 1984 and 2014, creating sufficient time periods for this process, meaning this does not greatly impact upon the estimates.

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5. Foreign Ownership and productivity in the North East of England

5.1 Introduction

Since the decline in heavy industry in the North East in the 1980s, foreign investment has been encouraged through Government subsidies to encourage regional growth and productivity. As discussed in Chapter 3, previous studies found that foreign-owned plants were seen to possess advantageous characteristics, to such an extent that those characteristics overcame the cost of the investment of setting up a plant abroad. This research was consolidated by studies such as Girma et al (2015) in China, Guadalupe et al (2012) in Spain, and Arnold and Javorcik (2009) who also found that foreign ownership had a positive impact on productivity. This chapter examines the foreign ownership effects on the productivity of manufacturing plants in the North East of England, when compared with domestically-owned manufacturing plants.

Firstly, the effect of foreign ownership is estimated between UK-owned and all foreign-owned plants, and the effects of foreign ownership are further estimated using three different foreign ownership groups: EU, US and Rest of the World (ROW). The effect of foreign ownership is then estimated within different industries, to capture any heterogeneity. Finally, the ownership effect of foreign-owned plants as a whole, and also the different foreign ownership groups is estimated over time, between 1986 and 2014. This period has been chosen to capture the announcement of the EU Single Market in 1986, the introduction of the Single Market in 1993, and to avoid any impact Brexit may have on plants' behaviour following the announcement of EU referendum.[24]

The chapter order is as follows: section 5.2 presents the estimation method used to calculate the foreign ownership effect, section 5.3 presents the results, and section 5.4 concludes the chapter.

5.2 Estimating the foreign ownership effect on productivity

This section presents the models used to estimate the effect of foreign ownership on total factor productivity within manufacturing plants in the North East of England.

The first step is to estimate the effect of foreign ownership on total factor productivity. Then, foreign ownership will be separated into Non-EU and EU to establish whether there is an ownership effect of these groups when compared with UK ownership. The UK-owned plants are used as the base, or comparison group for the foreign ownership effects.

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[24] In 2015, the UK Government passed the European Union Referendum Act 2015. This Bill was to make provision for the holding of a referendum in the United Kingdom and Gibraltar on whether the United Kingdom should remain a member of the European Union.

The models are estimated using a dynamic System GMM model due to the presence of endogenous, time varying, variables (Kukenova & Monteiro, 2008). Dynamic models allow for the lagged variables to be included in the model (Bond, 2002), as the previous realisations of the dependent variables influence the current one (Roodman, 2009). The results presented from these models in the tables below have been solved to show the long term effects.

5.2.1 Methodology

Equation 5-1 presents the model for estimating the effect of foreign ownership on productivity within manufacturing plants in the North East of England. This equation will be estimated using system-GMM with log real output (y_{it}) as the dependent variable to produce long run marginal effects of foreign ownership. The variables Capital (k), Labour (l), and Intermediates (n) are being treated as endogenous.

$$
\begin{gathered}
y_{it} = \alpha_1 y_{it-1} + \alpha_2 k_{it} + \alpha_3 k_{it-1} + \alpha_4 l_{it} + \alpha_5 l_{it-1} + \alpha_6 n_{it} + \alpha_7 n_{it-1} \\
+\alpha_8 FO_{it} + \sum_{y=1986}^{2014} \gamma_y \left[YEAR_t^y\right] + \boldsymbol{X}'\boldsymbol{\beta} + \varepsilon_{it}
\end{gathered}
\tag{5.1}
$$

Equation 5-1 Model for estimating total foreign effects within manufacturing plants in the North East of England

The main variable of interest in the model is FO (foreign ownership). This is a dummy variable that takes a value of 1 when the plant is owned by a Non-UK based company. Lagged variables for the production function, capital (k), labour (l), and intermediates (n), are also included. The ***X*** variable is a matrix that contains the variables: Multi-SIC, Multi-region, Single Plant, SIC dummies, and Herfindahl Index. To control for spatial or place benefits, dummy variables for the three main industrial areas of the North East are included: Newcastle, Sunderland, and Teesside. These are based upon the Local Authority codes for those areas. To capture the industry effects of foreign ownership, the foreign ownership dummy variable is interacted with the 2-Digit SIC code. To capture the impact of foreign ownership over time, the foreign ownership dummy is interacted with the year variable and the coefficients for each are then plotted.

The literature in section 3.2 suggested that the impact of foreign investment within a host region or country can be dependent upon the region’s characteristics. As the North East is an old manufacturing region, with an economy based upon heavy industry, it could be presumed that plants based in the North East will not be close to the productivity function frontier (Strauss, 2019). It would be beneficial to compare the effect of foreign ownership in the North East with different regions of the UK, including one assumed to be closer to the production frontier, to establish whether there is any regional effect.

To do this, the effect for foreign-owned plants, EU, US and ROW in the South East and the North of England will be estimated. The South East is presumed to be closer to the productivity frontier and so to be one of the most productive regions in the UK, outside of the London area. Recently there has been a focus by the UK Government to "level up" the North of England, due to the widening inequality between the North and the South of England. This is not a new UK Government focus. During the Coalition Government 2010 to 2015, the then chancellor, George Osbourne, platformed the idea of grouping the North into a collective group, with Greater Manchester as a centre point, similar to London in the South East, in order to create the "Northern Powerhouse" (Osborne, 2014), which focuses on the whole North of England. Therefore, it is beneficial to examine whether there is any difference between the foreign ownership effect in the entire of the North, centred on this focal point, and specifically the North East of England.

5.2.2 Results

This section**Error! Reference source not found.** presents the influence of foreign ownership of plants, c omparing them with UK ownership, in the North East of England. Columns (1) and (2) group together ownership groups, and column (2) controls for location. Columns (3) and (4) separate foreign ownership into three groups: EU, ROW, and US. To control for spatial or place benefits, dummy variables for the three main industrial areas of the North East are included: Newcastle, Sunderland, and Teesside. These are based upon the Local Authority codes for those areas. The full results can be found in Appendix A.7.

VARIABLES	FO (1)	FO (2)	EU/ROW/US (3)	EU/ROW/US (4)
INTERMEDIATE INPUTS	0.570***	0.571***	0.549***	0.548***
	(11.25)	(10.92)	(10.07)	(9.616)
EMPLOYMENT	0.490***	0.485***	0.444***	0.436***
	(7.691)	(7.618)	(7.321)	(7.081)
CAPITAL	0.0813*	0.0879*	0.109*	0.126**
	(1.67)	(1.771)	(1.796)	(2.048)
FO	0.0352	0.0351	-	-
	(1.573)	(1.57)	-	-
EU	-	-	0.0129	0.0094
	-	-	(0.389)	(0.282)
ROW	-	-	0.0730**	0.0721**
	-	-	(2.212)	(2.061)
US	-	-	0.0747**	0.0705**
	-	-	(2.572)	(2.408)
MIDDLESBROUGH	-	0.0148	-	0.00073
	-	(0.649)	-	(0.0335)
NEWCASTLE	-	0.0175	-	0.0238
	-	(0.699)	-	(0.953)
SUNDERLAND	-	0.0568***	-	0.0595**
	-	(2.177)	-	(2.357)
AGE	-0.146***	-0.15***	-0.186**	-0.201***
	(-2.431)	(-2.503)	(-2.336)	(-2.562)
MULTI SIC	-0.0179	-0.0179	-0.00622	-0.00911
	(-0.842)	(-0.845)	(-0.252)	(-0.365)
MULTI REGION	0.0707***	0.0681***	0.0920***	0.0890***
	(2.478)	(2.341)	(3.053)	(2.851)
SINGLE	-0.0815***	-0.0817***	-0.0341	-0.0375
	(-2.628)	(-2.544)	(-1.055)	(-1.103)
HERFINDAHL	0.266***	0.261***	0.210**	0.209**
	(2.683)	(2.603)	(2.158)	(2.072)
CONSTANT	-0.800***	-0.787***	-0.667*	-0.608*
	(0.277)	(0.276)	(0.361)	(0.360)
OBSERVATIONS	9,390	9,390	9,390	9,390
AR(1) Z-STATISTIC	-3.190***	-3.188***	-1.609	-1.558
AR(2) Z-STATISTIC	-0.281	-0.260	-1.178	-1.199
HANSEN TEST	31.58	31.09	22.08	21.90

Cells populated with an "–" indicate variables that have been dropped or not calculated by the regression. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5-1 Estimated long-run parameters for foreign ownership effect on ln Gross Output from estimating eq. (5.1) for the North East manufacturing 1984-2014. Variables of interest: FO, EU, US, ROW

Foreign ownership accounts for 5% of plants and 25% of employment in the North East manufacturing sector. This ownership effect has a positive impact on productivity when compared with UK ownership, however the impact was insignificant. This was also true when including the regional industrial areas through dummy variables, the coefficients of which were all positive, but with Sunderland alone being significant.

These results are similar to the empirical literature, which found that foreign ownership has an advantage over domestic plants. These studies include work by Lee (2007), Khawar (2003), Girma et al (2015) and Fons-Rosen et al (2021), which found that foreign ownership had an outright advantage over domestically-owned plants. Although the sign is positive, my work has found this positive impact to be insignificant. Therefore, based on works by Globerman et al (1994), Doms and Jenson (1998), I separated overall foreign ownership into ownership groups (EU, Rest of the World [ROW], and US) to examine their influence on plant productivity.

This work found that both US and ROW ownerships have a positive and significant impact on productivity, while EU ownership had a positive but insignificant impact on productivity when compared with UK-owned plants. Harris and Robinson (2003), and Harris and Moffat (2017) also found US-owned plants have a positive and significant impact on productivity while EU-owned plants tend to have the lowest impact on productivity. When examining the regional industrial areas, all are positive, but again only Sunderland is significant.

The Sunderland region most likely shows this effect because of the large, profitable and productive Nissan plant located there (Invest North East England, 2018). This plant is located far from its home base in Japan, and intended originally to exploit European markets through British access to the EU single market. This means that it cannot cost effectively rely upon parts and support from its home base. It therefore benefits from sharing its technological advantages, production techniques, and management with local production facilities and firms. The impact of foreign ownership can depend on the industry type. Harris and Robinson (2003) found in the UK manufacturing sector that the advantages of foreign-owned plants was dependent on the industry in which they were based. This estimation interacts the foreign-owned dummy variables with 2-digit 1980 SIC industries, and**Error! Reference source not found.** shows the results from this estimation, with Column (1) showing the results for the foreign-owned plants and column (2) presenting the results obtained by dividing the foreign ownership group into the three separate groups: US, EU, and ROW.

VARIABLES	FO (1)	EU/ROW/US (2)		
INTERMEDIATE INPUTS	0.666***	0.564***		
	(14.48)	(3.479)		
EMPLOYMENT	0.400***	0.124		
	(7.201)	(1.005)		
CAPITAL	0.0993*	0.228*		
	(1.889)	(1.790)		
AGE	-0.171***	-0.171**		
	(-2.539)	(-2.539)		
MULTI SIC	-0.0267	-0.0267		
	(-1.018)	(-1.018)		
MULTI REGION	0.0795***	0.0795***		
	(2.941)	(2.941)		
SINGLE	-0.0590*	-0.059*		
	(-1.692)	(-1.692)		
HERFINDAHL	0.147	0.147		
	(1.340)	(1.340)		
INDUSTRY INTERACTION	**FO**	**EU**	**ROW**	**US**
SIC 23 EXTRACTIONS OF MINERALS	-0.0852	*	*	*
	(-0.731)			
SIC 24 NON-METALLIC MINERAL PRODUCTS	0.0838	-0.513*	0.507	0.336
	(1.561)	(-1.736)	(1.356)	(1.372)
SIC 25 CHEMICAL INDUSTRY	-0.00961	0.477	-0.598	-0.427
	(-0.158)	(0.749)	(-1.460)	(-1.241)
SIC 31 METAL GOODS	-0.00760	0.500	-0.231	0.0917
	(-0.111)	(0.929)	(-0.662)	(0.472)
SIC 32 MECHANICAL ENGINEERING	0.0485	0.204	-0.127	22.72
	(1.087)	(0.524)	(-0.241)	(0.933)
SIC 33 OFFICE MACHINERY	0.206**	4.837	-	*
	(1.981)	(1.262)		
SIC 34 ELECTRICAL AND ELECTRONIC ENGINEERING	-0.155*	1.118	0.170	0.434
	(-1.649)	(1.232)	(0.495)	(1.382)
SIC 35 MOTOR VEHICLES AND PARTS	-0.0784	1.356	0.364	3.64**
	(-1.372)	(1.223)	(1.218)	(1.966)
SIC 36 OTHER TRANSPORT EQUIPMENT	0.0383	0.373	*	-

	(0.430)	(0.654)		
SIC 37 INSTRUMENT ENGINEERING	-0.254**	-1.145	-	-0.114
	(-2.021)	(-0.633)		(-0.336)
SIC 41 FOOD AND DRINK	-0.237***	0.0472	-	0.279
	(-3.115)	(0.147)		(0.995)
SIC 42 FOOD AND DRINK	-0.0252	1.034	*	0.539
	(-0.245)	(1.681)		(1.498)
SIC 43 TEXTILES	-0.00466	*	-	*
	(-0.0168)			
SIC 46 TIMBER AND WOODEN FURNITURE	-0.146***	0.182	*	-1.869
	(-3.475)	(0.522)		(-1.666)
SIC 47 PAPER AND PAPER PRODUCTS	0.186***	0.219	-0.232**	0.371**
	(3.394)	(0.455)	(2.076)	(2.076)
SIC 48 RUBBER AND PLASTIC	-0.153***	0.133	0.309	0.143
	(-2.600)	(0.658)	(0.968)	(0.522)
SIC 49 OTHER MANUFACTURING	-0.00417	*	*	-3.524
	(-0.0528)			(-0.314)
OBSERVATIONS	9,390	9,390		
AR(1) Z-STATISTIC	-3.481***	-4.052***		
AR(2) Z-STATISTIC	-0.000593	2.333*		
HANSEN TEST	42.86*	37.27		

Cells populated with an "–" indicate variables that have been dropped or not calculated by the regression and cells populated with a an asterisk symbol (*) indicate values that have been suppressed due to the Secure Data Service (SDS) requirements of there being more than 10 enterprises. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5-2 Estimated long-run parameters for foreign ownership effect on ln Gross Output within manufacturing sectors by interacting foreign ownership with individual SIC codes based upon eq. (5.1) for the North East manufacturing 1984-2014.

Foreign-owned plants had negative impact on productivity in 12 industries,[25] in five of which the impact is significant.[26] Most of the industries where foreign-owned plants have a productivity disadvantage are industries in which the North East is recognised to have knowledge and expertise,

[25] The industries where foreign ownership have a productivity disadvantage compared to UK ownership are: SIC 23, SIC 25, SIC 31, SIC 34, SIC 35, SIC 37, SIC 41, SIC 42, SIC 43, SIC 46, SIC 48 and SIC 49.

[26] The industries where the foreign ownership was negative and significant are: SIC 34, SIC 37, SIC 41, SIC 46, and SIC 48.

such as the Chemical Industry, Metal Goods Manufacturing, and Motor Vehicles, with the disadvantage being significant in the Rubber and Plastic Processing.

Foreign ownership had a positive impact on productivity within five industries,[27] in two of which foreign ownership had a significant advantage.[28] These industries are not ones in which the North East was known to have a body of knowledge and expertise, and appear to be in more low-value industries, such as the Paper and Paper Products industry.

EU ownership has a productivity advantage in 12 industries,[29] the highest number of industries when compared with the other ownership groups, however none of these coefficients are significant. In two industries, EU ownership has a productivity disadvantage when compared with UK-owned plants. In one of those industries, SIC 24 Non-Metallic Mineral Products, the disadvantage is statistically significant.

ROW ownership has a positive but insignificant impact in four industries[30] and a negative impact in another four industries,[31] in one of which, SIC 47 Food and Drink, the negative impact is statistically significant. The industries where ROW plants have a productivity advantage are those industries in which the North East specialises, such as rubber and plastic processing, electronic manufacturing and motor vehicle manufacturing.

US ownership has a productivity advantage in nine industries,[32] with two industries, SIC 35 Motor Vehicles and SIC 47 Paper and Paper Products showing the productivity advantage as significant. US ownership has a productivity disadvantage in four industries;[33] however, this disadvantage is not significantly different when compared with UK ownership.

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[27] The industries where foreign ownership has a productivity advantage over UK owned plants are: SIC 24, SIC 32, SIC 33, SIC 36, and SIC 47.

[28] These industries are SIC 33 and SIC 47.

[29] The Industries where the EU ownership has a productivity advantage are: SIC 25, SIC31, SIC 32, SIC 33, SIC34, SIC 35, SIC 36, SIC 41, SIC42 SIC, 46, SIC 47, and SIC 48.

[30] The industries where ROW plants have a productivity advantage over UK owned plants are: SIC 24, SIC 34, SIC 35, and SIC 48.

[31] The industries where ROW plants have a productivity disadvantage compared to UK owned plants are: SIC 25, SIC 31, SIC 32, and SIC 47.

[32] The industries where US owned plants have a productivity advantage are: SIC 24, SIC 31, SIC 32, SIC 34, SIC 35, SIC 41, SIC 42, SIC 47, and SIC 48.

[33] The industries where the US owner plants have a productivity disadvantage are: SIC 25, SIC37, SIC46 and SIC 49.

Ownership effect on productivity in different UK regions

This sub-section examines the ownership effect within different regions in the UK. Appendix A.5 and Appendix A.6 shows the descriptive statistics for the two regions to gain a comparison between the North East, and the North as a whole, and the South East for reference. There have been studies which show that regional characteristics influence the impact of FDI. Hayakawa, Lee and Park (2013), and Konings, (2001) showed that host region characteristics influenced the impact of foreign ownership on productivity.

Error! Reference source not found. The following table shows the impact of foreign ownership in the S outh East and the North of England. Columns (1) and (2) show the ownership effect in the South East and columns (3) and (4) show the impact of foreign ownership in the North of England.

VARIABLES	SE (1)	SE (2)	NORTH (3)	NORTH (4)
INTERMEDIATE INPUTS	0.627***	0.629***	0.572***	0.575***
	(9.018)	(9.538)	(7.100)	(10.39)
EMPLOYMENT	0.315***	0.318***	0.388***	0.427***
	(3.384)	(3.879)	(4.056)	(6.384)
CAPITAL	0.208*	0.195**	0.140*	0.0673*
	(1.839)	(2.027)	(1.774)	(1.701)
AGE	-0.269*	-0.236*	-0.198**	-0.175***
	(-1.867)	(-1.876)	(-1.780)	(-3.368)
MULTI SIC	-0.044**	-0.042**	0.00956	0.0244**
	(-2.159)	(-2.229)	(0.481)	(2.140)
MULTI REGION	0.0542*	0.0578**	0.0458	0.0553**
	(1.938)	(2.293)	(1.449)	(2.497)
SINGLE	0.0131	0.00988	-0.0116	0.00833
	(0.425)	(0.364)	(-0.443)	(0.498)
HERFINDAHL	0.126*	0.115	0.192*	0.187**
	(1.658)	(1.552)	(1.894)	(2.402)
FOREIGN-OWNED	-0.0242	-	0.0224	-
	(-0.684)		(0.561)	
EU-OWNED	-	-0.0743**		0.0226
		(-2.001)	-	(0.795)
ROW-OWNED		0.00823		0.00749
	-	(0.155)	-	(0.220)
US-OWNED		0.0393		0.0728***
	-	(1.035)	-	(3.075)
OBSERVATIONS	23,175	23,175	49,369	49,369
AR(1) Z-STATISTIC	-1.440	-1.685*	-2.749***	-1.858*
AR(2) Z-STATISTIC	-0.182	-0.161	0.491	-1.263
HANSEN TEST	19.62	18.09	17.37	4.847

Cells populated with an "–" indicate variables that have been dropped or not calculated by the regression. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5-3 Estimated long-run parameters for foreign ownership effect on ln Gross Output from estimating eq. (5.1) for the North and South East manufacturing 1984-2014. Variables of interest: FO, EU, US, ROW

For the South East, the overall impact of foreign ownership on productivity within plants is negative, but not significant, compared with UK ownership in the South East. However, when separating ownership into the different ownership groups, the results vary across the different groups. It is only EU ownership that has a negative and significant effect on productivity compared with UK-owned plants. ROW and US ownership had a positive, but insignificant, impact on productivity compared with UK-owned plants in the South East. In the North of England, the effect of foreign ownership on productivity was positive but insignificant compared with UK-owned plants. EU and ROW ownership have a positive but insignificant impact on productivity compared with UK-owned plants while US-owned plants have a positive and significant impact on productivity compared with UK-owned plants in the North of England.

As the South East is deemed the most productive region in the UK, it is expected that the most productive plants, both domestic- and foreign-owned, would be based in this region. Therefore, it could be argued that the foreign-owned plants are establishing themselves in the South East to benefit from the productive UK-owned plants located there. Going back to the Driffield and Love (2007) taxonomy of motivations, foreign ownership could be technology sourcing, meaning their presence would have no beneficial impact on the host country, and these plants would show a worse productivity performance than the domestic plants. This may not be the case for all ownership types.

Estimating the effect of foreign ownership on productivity over time in the North East of England

The figures below in this section, show the changes in the levels of productivity in foreign-owned plants, in relation to that in UK-owned plants, in the North East of England. This has been calculated by interacting the foreign ownership dummies with the time variable, Year, to calculate an annual coefficient, which is then plotted to show how productivity compares to the UK-owned baseline. The solid blue lines represent the coefficients from these estimations, and the dotted lines are the 95% confidence intervals. The underpinning estimates for these figures can be found in Appendix 3 with the output tables from each estimation.

Figure 5-1 The effect of foreign ownership on plants over time in the North East shows the changes in productivity over time for all foreign-owned plants when compared with UK-owned plants.

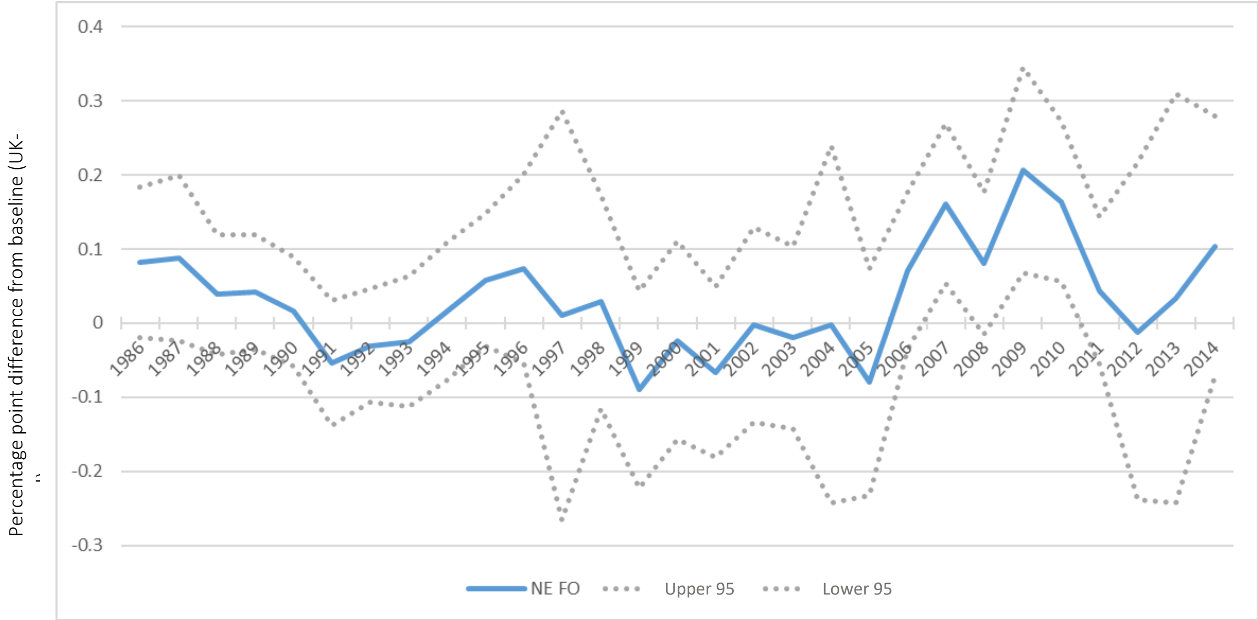

Figure 5-1 The effect of foreign ownership on plants over time in the North East

For most years, productivity in foreign-owned plants is not statistically different when compared with productivity in UK-owned plants. The years where there was a significant difference in productivity between foreign-owned and UK-owned plants are between 2007 and 2008 and 2009 and 2011. During these periods, the productivity in foreign-owned plants is greater than UK-owned plants.

Figure 5-2 showing the effect of EU ownership.

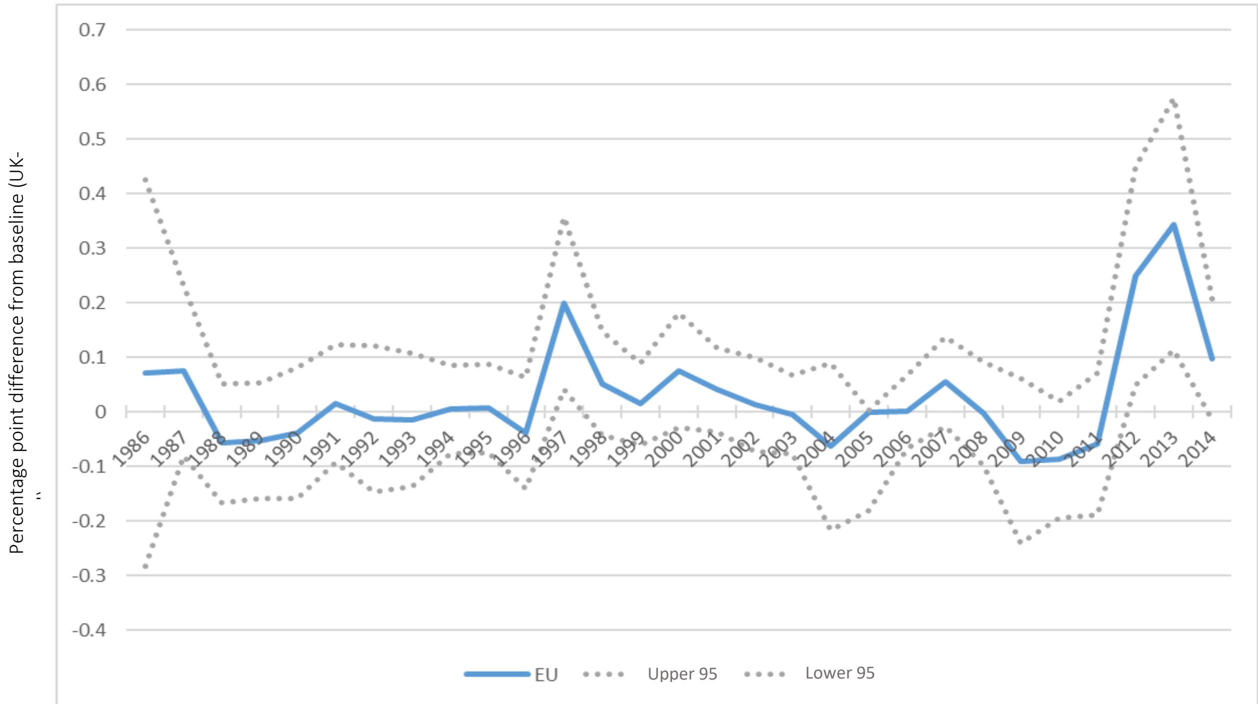

Figure 5-2 The effect of EU ownership on plants over time in the North East of England

The impact of EU ownership is not statistically different to UK ownership for most of the time period. The exceptions are 1997 and between 2012 and 2014 when EU ownership had a positive impact on productivity when compared with UK-owned plants, and in 2005 when it had a negative impact on productivity.

The close proximity of mainland Europe provides a disincentive for the EU-owned plants in the North East to innovate and invest to establish more productive, but higher cost plants in the UK. The satellite EU-owned plants are sufficiently close to the company home base in Europe for the company to benefit from R&D, advanced technology, and production processes based there, without incurring parallel expenditure in such features in the UK. This reduces the likelihood of positive spillovers into the UK supply chain and interlinked plants. Because the UK is geographically close to the EU-owned plants' home markets, the EU-owned plants are encouraged to guard and restrict access to their advantageous characteristics (which stem from their R&D and improved production development), so limiting learning by, and competition from, UK-owned neighbours, which could potentially use these learned abilities to enter the EU-owned plant's home markets.

Figure 5-3 showing the effect of ROW ownership[34].

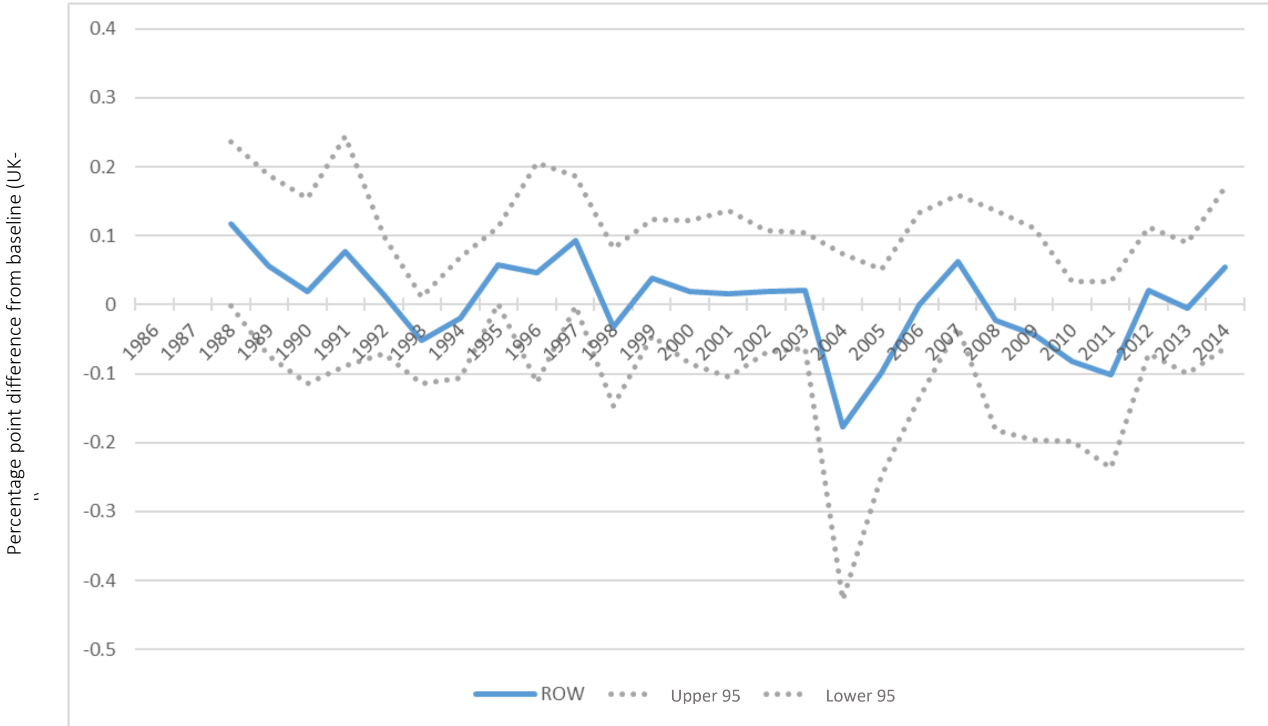

Figure 5-3 The effect of ROW ownership on plants over time in the North East of England

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[34] The year 1987 removed due to the number of enterprises not meeting the require threshold imposed by the SDS for outputs.

For ROW ownership, there are no years where ROW plants have a statistically different ownership effect on productivity when compared with UK-owned plants. Over time, the level of employment and level of GVA of ROW-owned plants increased, as can be seen in Figure 2-8 and Figure 2-10, however there is a gradual decline in the ROW ownership effect on productivity when compared with UK-owned plants. This could indicate that the ROW plants opening, or the jobs being created, in the North East were to exploit the regional characteristics of low cost land and labour, as well as access to the EU single market, without investing in advances to maintain or create higher productivity. This could result in no positive spillovers, or negative spillovers between ROW-owned plants and UK-owned plants. Globerman et al (1994) found in their analysis of Canadian firms and multinational firms that the relationship between Japanese-owned firms and wages was negative. Their proposal for this is related to workplace conditions, where they found this relationship came from Japanese establishments offering a safer/cleaner work environment, or possible greater anticipated job security which was accepted by workers in exchange for a lower wage rate. This suggests that these Japanese firms offered long term job security. These Japanese established plants also tended to be younger.

Figure 5-4 shows the effect of US ownership

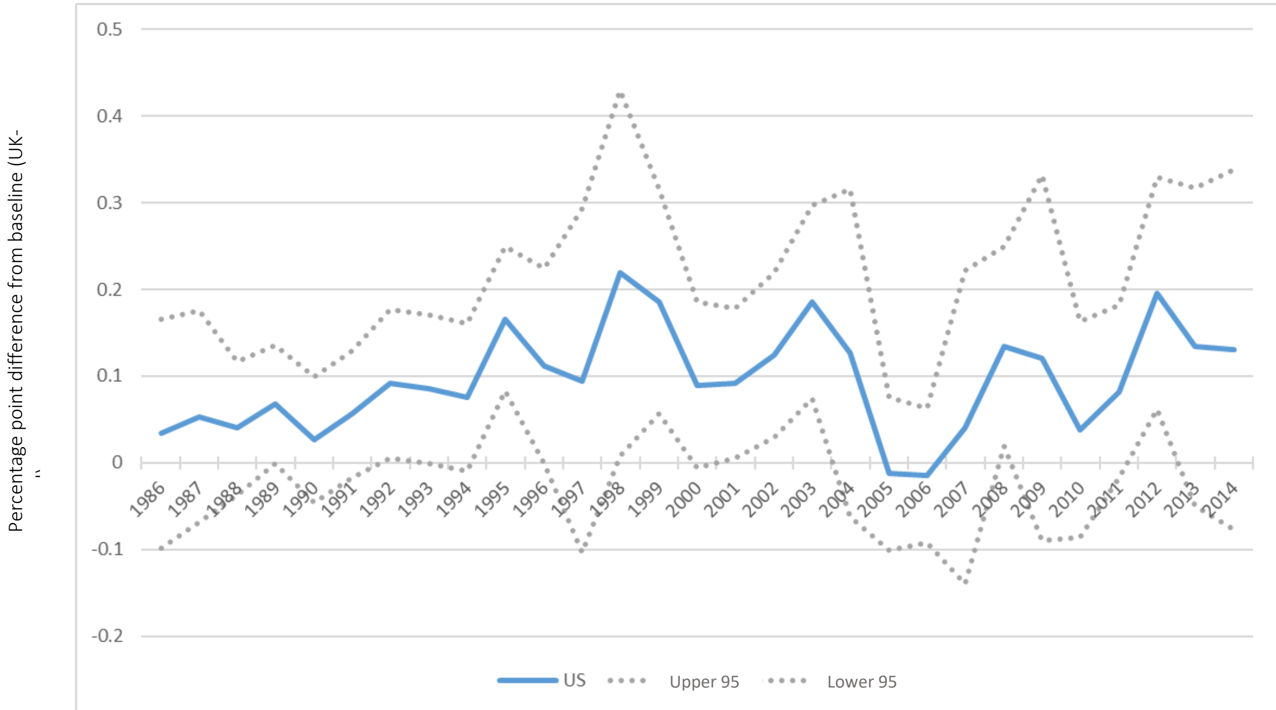

Figure 5-4 The Effect of US ownership on plants over time in the North East of England

The US ownership effect on productivity, for the majority of time period, outperformed the UK ownership effect. Only between 2005 and 2006 did the US-owned plants have a negative impact on productivity, when compared with UK-owned plants, however, this difference it was not statistically significant. There were several years when the US ownership had a significant productivity advantage over UK-owned plants: 1989, between 1992 and 1996, between 1998 and 2003, 2008 and 2012.

Measured over the same time period, US-owned plants experienced an overall decline in employment, with the exception of a rise and fall between 2000 and 2006. The total level of US employment at the end of the time period was less than it was at the beginning of the period. This can be seen in Figure 2-8. The maintained productivity advantage of US-owned plants could be a result of the decision to either invest in, or use, increased technology in their plants, reducing the need for workers. This advantage may also be due to the "churning" effect, where less productive plants leave the market to be replaced by more productive plants improving overall productivity (Anderton et al., 2020).

The creation of the Single Market in 1993 provided an incentive for US- and ROW- owned plants to establish in the UK, as they then benefitted from reduced tariffs, access to a larger labour pool, and the increased accessibility of capital that were associated with the EU Single Market.

EU-owned plants, however, already had access to the Single Market, therefore did not benefit from location in the UK in the same way. They may have chosen to establish plants within the UK to solely target the UK market, and to reduce transportation costs associated with this trade into the UK, or to exploit host country characteristics such as low wages and low land costs.

5.3 Conclusion

There is some evidence in the literature that foreign-owned plants are more productive than domestically-owned plants, due to their superior technology, which allows them to set up a competitive cost base, meaning they can compete successfully with established domestic firms (Hymer 1979, Dunning 1988). Fons-Rosen et al (2021) found foreign acquisitions saw an increase in productivity over a four year period in eight advanced European countries. Xu, Liu, and Abdoh (2022) found in another cross-country study of 139 countries that there was a strong positive relationship between FDI and productivity.

However, the literature also found that the impact of ownership can depend on factors such as ownership group, location of plant, motivation for the FDI, and the industries in which the plants are based. This chapter has taken a disaggregated approach, by considering different ownership groups - all foreign-owned, EU, US, and ROW - and estimating how these ownership groups influenced productivity when compared with UK ownership. Then, as the literature indicates, these ownership groups have been interacted with 2-digit 1980 SIC industries to examine the impact of foreign ownership in different industries. Also indicated in the literature is the impact host country or host region characteristics can have on the impact of foreign ownership on productivity. Because of this, the impact of productivity in these foreign-owned firms has been estimated for the North and the South East of England.

The overall direct effect of foreign ownership of firms in the North East is positive, suggesting foreign-owned plants have a productivity advantage over domestically-owned plants within the region, but the overall impact of foreign ownership is insignificant. When separating the foreign ownership into EU, US, and ROW, however, US and ROW ownership have a positive and significant impact on productivity, while EU ownership has a positive but insignificant impact on plant-level productivity. Additional industrial areas were added to the regression, all of which showed a positive impact on productivity, but only Sunderland showed a positive and significant impact, the coefficients for the foreign ownership groups remaining the same.

The ownership productivity advantage differs between industries. This was found in the literature, which showed different ownership groups having a productivity advantage depending on the industry (Harris & Robinson, 2003). This was seen across all ownership types. EU ownership was seen to have an overall positive impact on productivity within industries, as did US ownership.

Comparing these findings with the impact of foreign ownership in other regions of the UK, the South East of England shows foreign ownership having a negative impact on productivity when compared with UK ownership. When foreign ownership is separated into different ownership groups, EU-ownership has a negative and significant impact on productivity while ROW and US have a positive but insignificant impact in the South East of England.

When examining the impact of foreign ownership in the North of England, the impact was similar to that seen in the North East of England in that foreign ownership has a positive but insignificant impact on productivity. Splitting the foreign ownership into the three ownership groups, all of these have a positive impact on productivity, but only US ownership is both positive and significant whereas in the North East, US and ROW ownership had a positive and significant impact.

Overall, the impact of foreign ownership in the North East is positive, but when all ownership groups are taken together the impact is insignificant. When separating foreign ownership groups into EU, US, and ROW, all the ownership groups are positive, but now the ownership effect of ROW and US are significant at the 5% level.

Overall, EU-owned plants are the least productive when compared with the other ownership types. It could be that EU-owned plants are producing lower value-added goods or are not partaking in high value R&D. Mainland Europe is close, and over the time this data covers, there was freedom of movement of goods and people between the UK and the wider EU. This would suggest that the North

East was used to produce low value intermediate parts which were then sent to mainland Europe, where the higher value manufacturing was taking place. The possible lower cost barriers for the EU-owned plants, when compared with US and ROW plants, may mean that there is less of an incentive for them to produce higher value goods.

Regarding ROW- and US-owned plants, the possible higher cost barriers they face make it more cost effective for these firms to set up a plant that undertakes supporting high value R&D and produces completed high value goods within a single plant, before shipping the finished product to mainland Europe. This is something that is being seen in the case of the Nissan factory in Sunderland, with the expansion of the battery factory for their electric car line (Jolly, 2023) .

These estimates, however, do not show the way in which UK-owned plants are impacted by the presence of these EU- and ROW-owned plants. As Javorcik (2004) and Dunning (1988) stated, foreign-owned firms may put in place mechanisms that prevent their advantaged technology and knowledge from spilling over to competing UK-owned plants. UK-owned plants could then experience crowding out by the foreign-owned plants as they are unable to successfully compete with them.

To explore this, the presence of foreign-owned plants could be examined by industry, but this would fail to capture the inter-industry linkages. As Javorcik (2004) found in their analysis, spillovers are more likely to occur vertically rather than horizontally, and these plants may not be within in the same SIC classification. A solution to this is to use a cluster configuration, which would capture the linkages between a number of different SIC classifications and provide a comprehensive view of the plants which are likely to interact with each other. The next chapter presents a clustering methods that is comparable and can be evaluated.

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6. Cluster configurations for the UK Manufacturing Industry

6.1 Introduction

Clusters of industries are characterised as networks of production of strongly interdependent firms connected through a number of different linkages such as Input-Output links, value added production chains, and labour and input sharing due to co-location (Roelandt & Den Hertog, 1999). Some governments have put in place incentives to encourage the creation of clusters, (Martin et al., 2011) who highlighted the French government's decision to invest 1.5 billion euros to encourage competitive clusters over the time periods 2005 and 2008 and again between 2009 and 2011. This chapter presents a methodology that considers a variety of inter- and intra- industry linkages to create a comparable set of clusters and applies these to the UK manufacturing sector.

The use of industry clusters allows researchers to analyse the relationship between industries within regions and provides a better understanding of the way in which industries are interlinked within a region. Using cluster analysis has advantages over the more traditional sectoral analysis as it can take into account horizontal and vertical linkages, knowledge flows, and interdependencies (Rouvinen & Ylä-Anttila, 1999), whereas the traditional sectoral approach focuses on strategic groups of similar firms with similar network positions (Roelandt & Den Hertog, 1999).

There are, nevertheless, some limitations in relation to cluster analysis. A number of researchers have presented methods using different types of data to generate industry clusters, making it difficult to compare clusters between different studies (Bergman & Feser, 2020). Clusters are also usually created and defined based upon the specific research focus or particular Government policies, which again makes it very difficult to compare clusters between studies (De Propris & Driffield, 2005). This chapter uses a clustering method that was developed to overcome these problems, and this approach is then applied to the UK Manufacturing sector.

Section 6.2 will present the methods used to identify clusters of industries in the literature. Section 6.3 presents the Delgado et al (2016) clustering algorithm and its components, and Section 6.4 shows how the Delgado et al (2016) clustering algorithm is applied to UK manufacturing industries. Section 6.5 examines the manufacturing clusters on a national level, and Section 6.6 examines the clusters present in the North East.

6.2 Identifying Clusters

Defining clusters of industries is not an exact science and is usually dependent upon the research focus of the analysis, which can result in less attractive industry groupings being overlooked and excluded from cluster analysis (Koo, 2005) (Komorowski, 2020). Many have presented methods using different types of data to generate industry clusters, making it difficult to compare clusters between the different studies (Bergman & Feser, 2020). Bergman and Feser (2020) categorised the different methods of clustering into two groups: Mirco[35] and Meso/Macro.[36] Mirco methods focus more on individual regions or industries and examine why firms co-locate, while Meso/Macro approaches are not limited to a specific region or industry and use the available macro datasets. Delgado labels these methods as regional and national clustering matrices.

Many clustering studies focus on a single type of linkages, some examples being Input-Output (I-O) linkages, employment or occupational linkages, and knowledge spillovers (Koo, 2005). Hill and Brennan (2000), Feser and Bergman (2000), Holmen and Jacobsson (2000), and Titze, Brachert, and Kubis (2011) all used I-O linkages when identifying clusters in different countries. While I-O linkages can identify the presence of linkages between industries, it is dependent on the quality of the data. Where the data is too aggregated on an industry and a national level, it can result in some of linkages being missed or others being over exaggerated (Delgado et al 2016).

Occupational linkages are also used, as this allows for identification of some of the connections that are missed if clusters were made solely using the industry-based approaches (Wan et al., 2013). Peters (2005), Renski et al (2007), and Nolan et al (2010) all use occupational linkages to define sets of clusters. The failure to acknowledge these labour linkages reduces the usefulness of clusters, as they then do not capture the changes in demographics and prosperity (Wan et al., 2013). Occupational linkages can be captured though identifying industries with common occupational linkages, or by grouping occupations, rather than industries, to create skill clusters (Renski, (2013). However, again, the availability of this data is limited making it difficult to be able to undertake such research.

Spillovers can also be used to identify clusters. Spillovers can occur in two different ways: inter-industry and intra-industry spillovers. As discussed in chapter 3, inter-industry spillovers (Marshallian) occur between different industries, while intra-industry spillovers (Jacobian) occur within the same industry. An example of this clustering method is using knowledge spillovers either within an industry or between different industries, to identify clusters. This however is a technique that is less common. (Koo, 2005).

[35] These micro focused studies focus on why firms co-locate within industry clusters focusing on the similarity of production factors such as markets, labour, capital, and technologies.

[36] Bergman and Feser present seven Meso/Macro clustering methods: Expert opinion, Specialisation Indicators (LQs), IO table-Trade, IO table-Innovation, Graph theory/network analysis, and surveys.

It is difficult to establish where these knowledge spillovers occur, as there is no geographical data available on where firms obtain their external knowledge. Knowledge spillovers would need to be identified from the data which is available, and in addition, using only one type of data would result in some linkages not being captured. These knowledge spillovers can be proxied by used co-location data on employment and firms within an area, as it is assumed this collation of firms will cause knowledge spillovers. For some, the use of knowledge-based linkages should take priority when creating clusters, because of the way in which such spillovers can lead to the creation of core industries (Malmberg & Maskell, 2002). Koo (2005) argues that using knowledge spillovers means there is no need for I-O linkages or shared labour pools, due to the inter- and intra-knowledge flows from shared knowledge bases.

Delgado et al (2016) argues in her clustering algorithm that solely using one type of clustering technique can exclude some linkages and make the configuration over reliant on one type of linkage. Instead, she argues it is better to include multiple clustering methods that are on a regional level and on a national level, so that both inter- and intra-industry spillovers are being captured, and any biases present in one single clustering method are overcome.

6.3 Delgado's Clustering Algorithm

Delgado et al (2016) developed a clustering algorithm that assesses industries and organises them into clusters, based upon a mixture of Meso-level and Micro-level methods. They apply this to US industry data, using the 2007 North American Industry Classification System (NAICS) for the 2009 Country Business Patterns (CBP) across this whole economy, minus farming and Government activities. They chose to use traded industries[37] (industries that are geographically concentrated) which resulted in 778 traded industries being used to develop the clusters. They use 6-digit NAICS industry codes to create a cluster configuration containing 51 clusters, using inter-industry linkages based upon co-locations patterns, input-output links, and labour occupation similarities. This matrix appears to generate meaningful sets of clusters that capture the broad set of industry interdependencies. The C* with the highest overall VS score (78%) was calculated using a hierarchical clustering function and contains 51 clusters.

Delgado's clustering algorithm uses a combination of inter-industry and intra-industry linkages from multiple different clustering methods to create the cluster configuration. It assesses linkages based

[37] Delgado et al (2016) defines traded industries as those industries which are more geographically concentrated and produce goods and services that are sold across regions and countries. They do not solely cater to the local market, dubbed local industries.

upon industries that are strongly connected by trade though I-O tables, and it assesses groups of industries that co-located in terms of employment and number of plants within in an area. It can also use similar occupational patterns, and group industries depending on occupational types and patterns.

The algorithm can generate a number of different cluster configurations, labelled as *C,* which are made up of individual clusters *c*. These configurations and clusters are individually scored and evaluated to establish the configuration that captures most inter-industry linkages.

Delgado et al (2016)[38] present a five-step process to establish the cluster configurations. Firstly, they use what they describe as "cluster definitions[39]" to define a similarity matrix[40] (M_{ij}). This matrix is used to capture the relatedness between two industries *i* and *j*. Next, the user needs to define the broad parameter choices (β), which control how the clustering algorithm is estimated, and the number of clusters to be estimated. This then produces the clustering function ($C=F(M_{ij}, \beta)$), which is used to calculate the cluster configurations *(C)* based upon the similarity matrix and the broad parameters.

To then establish which cluster configuration (C^*) best captures the inter-industry linkages, performance scores are calculated for each configuration. Once the best configuration is identified, further analysis is then done to refine the individual clusters. After that, the final Benchmark Cluster Definition (C^{**}) can be used for analysis.

The advantage of this method is that it can be adapted to the SIC industry classification system. In the case of the UK manufacturing sector, it is possible to use five matrices; three are regional and two are national. The three regional matrices measure the co-location between industries i and j across regions, based on numbers of plants in these industries (LC-Est), co-location between industries i and

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[38] A more detailed explanation into the Delgado et al (2016) method can be found in the Appendix 8.

[39] The cluster definitions are inter-industry linkages that are classified into two groups: comparable clusters and Regions specific clusters. The comparable cluster definitions are based upon inter-industry linkages from multi-region analysis and allow for direct comparison across same clusters in different regions. The Region-Specific definitions observe the linkages among firms or industries within a single region. These can be used to enhance the information captured in the comparable cluster definitions; however, it is not recommended to use these types of definitions alone as key activities can be excluded even though they are important for the analysis.

[40] Delgado et al (2016) presented three types of similarity matrices for the cluster configuration for US industry data: Co-location, National-level, and multidimensional. The Co-location matrices are Location Correlation (LC)-Employment, LC-Establishments, and Co-agglomeration Index (COI). National Level similarity matrices are the Input-Output (IO) data and Occupational Links (OCCs). Multidimensional matrices are a combination of these co-location and national level. This is the most preferred type due to the combination of both types as it reduces the level of noise by averaging across multiple matrices.

j across regions, based on total employment in these industries (LC-Emp); and the Co-Agglomeration Index (COI) which captures the increased likelihood of two industries co-locating in a region compared with where their employment was distributed randomly.

$$COI_{ij} = \sum_r (s_{ri} - x_r)(s_{rj} - x_r)/(1 - \sum_r x_r^2) \quad (6.1)$$

Equation 6-1 Co-Agglomeration equation

For this work, the regional aggregation used is the Travel-to-Work-Area (TTWA) as it gives a better representation of economic flows than using a Local Authority or Postcode region. The national matrices measure Occupational links (Occ), shows the percentage of employment type within an industry, and the Input-Output linkages matrix (I-O) shows the share of industry *i*'s inputs and outputs sourced from industry *j*. One main advantage with the Delgado et al (2016) clustering configuration is its ability to assess and evaluate the different clusters created.

After the initial cluster configuration has been produced, it then becomes necessary to assess and evaluate the clusters. This is done by calculating performance scores, to ensure that each cluster is meaningfully different to the other clusters in that configuration and that the industries fit well into that cluster. The Validation scores (VS) are calculated for each configuration based upon alternative industry measures. The validation scores are percentages calculated using "within cluster relatedness" (WCR) [41] and "between cluster relatedness" (BCR)[42]. The WCR scores are calculated by taking the average across industry relatedness correlation matrices[43] to establish the BCR, and WCR. There are WCR scores calculated for each cluster, which show the overall fit of the cluster within the configuration, and for each individual industry, to show the fit of the individual industry within a

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[41] Within Cluster Relatedness is defined as the average relatedness between pairs of industries within a cluster. So, the Within Cluster Relatedness for focal cluster c_1 would $WCR_{c_1} = M_{a_1 a_2}$ where M is the matrix used to evaluate the focal cluster and *a* are the industries within the cluster.

[42] Between Cluster Relatedness is the average relatedness between industries in cluster *c* and those in another cluster within in the same cluster configuration. So the Between Cluster Relatedness between clusters c_1 and c_2 is $BCR_{c_1, c_2} = Avg(M_{a_1 b_1}, M_{a_1 b_2}, M_{a_2 b_1}, M_{a_2 b_2})$ where M is the matrix used to evaluate the focal cluster and *a* is the industry within the cluster c_1, and *b* is the industry within cluster c_2.

[43] These scores are calculated with using four distinct matrices: LC-Emp, LC-Est, IO and Occ. These matrices are not dependent upon the similarity matrix used to calculate C*. Sub-scores can be calculated and compared consistently no matter that the similarity matrix used to calculate *C.* WCR scores are calculated by cluster and by industry for each unidimensional matrix, and these are then averaged across to get the overall WCR score for that industry within the cluster configuration.

cluster. The validation scores are calculated by comparing the WCR with the average BCR, and the 95th percentile BCR. The cluster configuration score[44] is calculated by averaging the VS-cluster, which establishes whether individual clusters within a configuration are meaningfully different from other clusters, and VS-industry, which assesses the fit of individual industries within a cluster. The algorithm then ranks these configurations, resulting in the top ranked configuration being the one that is most likely represent clusters of industries.

Using these scores, it can be assessed whether there are any outliers within clusters:

- Systematic outliers - those are outliers that have a low overall WCR score using two criteria: those industries that have a low WCR score relative to other clusters, or those industries that have a low WCR score relative to the other industries in that cluster.
- Marginal outliers - those industries which would fit better in another cluster even though they have a high WCR score in their current cluster. These normally occur due to issues in the underlying data.

After the initial cluster configuration has been generated, it needs to be assessed to identify the presence of any systematic outliers. These are industries that were initially allocated into one cluster based upon their WCR score, however, would fit more appropriately in a different cluster within the configuration. This is done by comparing the industry WCR scores relative to other clusters, or where the WCR score was lower compared to industries within the same cluster.[45] These outliers are then reassigned to a cluster where their WCR is higher.

It may also be the case that there are industries with a high WCR score which do not fit into the cluster where they have been allocated. These have not been reallocated using the algorithm, as the industry has a high WCR score in relation to other industries within the cluster. These are the industries classed as marginal outliers and can be manually moved to a cluster that is more appropriate for that industry. These often occur due to limitations within the data, such as the overestimation of input-output links between two industries resulting from the aggregation level of the data.

[44] The VS for the cluster configurations calculated within this document can be found in Appendix 6, in tables A6.1 and A6.2. these tables show the breakdown of VS scores over the four evaluating matrices: LC-Emp, LC-Est, IO and Occ.

[45] This is done by comparing the WCR_{ic} is below the 75^{th} percentile value of the industry BCR or if the WCR_{ic} is two standard deviations below the average WCR_{ic} of the cluster.

6.4 UK cluster configuration

For the UK cluster configuration, the 1980 SIC system will be used as the industry classification for the clusters and a range of years will be used, due to limitations within the occupational data. The years chosen are 2010-2014, because of the limitations within the occupational data available. The available data in the UK differs from that of the US and, because of this, different cluster definitions will be used to develop the similarity matrices. The main difference between the UK and US data is that the US has a wider range of aggregate level data sets, or as Delgado names them "National Level" matrices.

There are three co-locational matrices available to create these similarity matrices: LC Employment, LC Establishment, and the co-agglomeration index (COI), and two national level matrices, of Input-Output tables and Occupational type. Unlike the US data, where the Input-Output tables are based upon industries, the UK Input-Output tables are based upon product type. This means that the products must be manually mapped to the different SIC codes, which may result in some misallocation of products to industries. There are 29 possible similarity matrices[46] that can be evaluated to find the cluster configuration.

After the similarity matrices[47] have been identified, the parameter choices need to be selected. This predefines the number of clusters to be estimated and how they will be evaluated. When choosing the optimal number of clusters, it must be taken into account that an overestimation or an underestimation will reduce the usefulness of the cluster configuration. If too many clusters are

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[46]These are the possible similarity matrices are: LC-Emp, LC-Est, COI, OCC, LC, LC-Emp-COI, LC-Emp-Occ, LC-Emp-IO, LC-Emp-COI-Occ, LC-Emp-COI-IO, LC-Emp-Occ-IO, LC-Est-COI, LC-Est-Occ, LC-Est-IO, LC-Est-COI-Occ, LC-Est-COI-IO, LC-Est-Occ-IO, LC-COI, LC-Occ, LC-IO, LC-COI-OCC , LC-COI-IO, LC-Occ-IO, COI-OCC, COI-IO, COI-IO-Occ, LC-Occ-COI-IO, LC-EMP-COI-OCC-IO, LC-Est-COI-OCC-IO.

[47] The similarity matrices are estimated using the hierarchical clustering function, a method that involves grouping elements of a dataset into successively smaller clusters depending of similarities or dissimilarities of the points within the dataset Cohen-Addad, V., Kanade, V., Mallmann-Trenn, F., & Mathieu, C. (2019). Hierarchical clustering: Objective functions and algorithms. *Journal of the ACM (JACM)*, *66*(4), 1-42. . This is due to the inclusion of the Input-Output tables and the co-agglomeration index within the similarity matrices. Their inclusion means the centroid-based clustering functions of kmean and kmedia. Methods that cluster points based upon a centre point of a group and move the data points with similar mean or medium into that cluster Pelleg, D., & Moore, A. (1999, 1999). Accelerating exact k-means algorithms with geometric reasoning. Proceedings of the Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Diego, California, USA., cannot be used as they require the underlying raw data not to have been manipulated, which is required in using the Input-Output tables and co-agglomeration index.

chosen these would not be meaningfully different, and if too few are chosen, then the industries within them may not meaningfully related to each other. It is difficult to identify the correct number of clusters within a configuration, as defining too many or too few weakens the value of the cluster configuration. Using the previous work by Feser (2003), Porter (2005), Delgado imposed a range for this number of 30 and 60 clusters per configuration. For the UK SIC classification, the range of possible clusters, taking into account the work done by Feser (2003), Porter (2005) and Delgado et al (2016), has been set between 45 and 65.

6.4.1 UK Manufacturing Cluster Configuration

The cluster configuration with the highest Validation Score is the LC-IO-46[48], which has the highest overall Validation Score. Table 6-1 below shows the top ten cluster configurations ranked using the Validation Scores. The configuration with the highest score is a multidimensional matrix with 46 clusters that combines two regional matrices of LC-Emp and LC-Est with the one national Input-Output matrix.

Cluster	Number	Max Ind	VS	Rank VS
IO LC-Est LC-Emp 46	46	11	88.51	1
IO LC-Est LC-Emp 49	49	9	88.27	2
IO LC-Est LC-Emp 47	47	11	88.22	3
IO LC-Est LC-Emp 48	48	10	87.94	4
IO LC-Est LC-Emp 45	45	11	87.87	5
IO LC-Est LC-Emp 44	44	11	87.74	6
IO LC-Emp 50	50	11	87.7	7
IO LC-Est LC-Emp 50	50	9	87.64	8
IO LC-Est LC-Emp 42	42	11	87.54	9
IO LC -Emp 49	49	11	87.47	10

Table 6-1 Top ten clusters configurations for the UK Manufacturing sector

Table 6-2 shows the cluster configuration with the highest validation scores calculated using the Delgado cluster configuration. The largest cluster in UK manufacturing, in terms of employment, is Cluster 3, Metal Manufacturing, while the largest cluster in terms of the number of plants is Cluster 23, Printing Products. The smallest cluster is Cluster 37, Synthetic Rubber in terms of number of plants and employment. The WCR_c score shows the fit of the cluster in the overall configuration, and these are the scores used when the configuration is evaluated. Examining the way in which each cluster fits within the cluster configuration, the cluster with the lowest over all WCR_c score is Cluster 8,

[48] More detailed tables breaking down the different Validation Scores can be found in Appendix 9.

Miscellaneous Manufacturing, and the cluster with the highest score is the Cluster 9, Bread and Biscuits. The higher the score, the greater the fit of the clusters within the configuration.

Cluster	Cluster name	WCR_c	Number of plants	Total Employment
1	**Ferrous metals and manufacturing**	2.227	47337	2730136
2	**Non-ferrous metal Manufacturing**	2.083	144130	3432349
3	**Metal Manufacturing**	1.951	604429	11816831
4	**Mineral Extraction**	1.817	24751	882671
5	**Other Minerals extraction**	2.284	2759	53638
6	**Mineral Manufacturing**	2.014	135839	2564540
7	**Building Materials**	2.159	74605	1270949
8	**Miscellaneous Manufacturing**	0.845	286521	6752143
9	**Bread and Biscuits**	2.851	124819	3765286
10	**Large Transport Manufacturing**	2.284	50524	1472255
11	**Soaps and Perfumes**	2.517	17863	942793
12	**Grain and Starch**	2.09	4995	207010
13	**Pet feeds**	2.599	21219	517638
14	**Leather working**	2.199	27284	359714
15	**Paints**	2.368	20353	708192
16	**Processing of food stuffs**	2.262	24743	1234801
17	**Explosives and ordnance**	1.963	6032	583749
18	**Cooking fats and oils**	1.925	2254	121515
19	**Processing meats**	2.463	37412	2736954
20	**Sugar**	2.284	579	109309
21	**Confectionary**	2.714	57135	2877066
22	**Paper Products**	2.191	78362	2483328
23	**Printing products**	2.388	771320	9434424
24	**Distilling and compounding**	2.284	6575	348332
25	**Brewing and Tobacco**	1.807	19670	1091137
26	**Recreational Manufacturing**	2.228	318502	2319685
27	**Precision Apparatus**	2.187	95291	1978970
28	**Inorganic and organic chemicals**	1.805	22231	1527666
29	**Essential oils**	2.284	2121	86875
30	**Chemical and Adhesives**	2.07	36932	1158463
31	**Man Made Fibre Production**	2.284	1012	152368
32	**Rubber tyres**	2.284	2282	421318
33	**Plastic and rubber products**	2.574	207927	5771510
34	**Electronic Equipment**	2.054	231853	6285035
35	**Wood manufacturing**	2.071	301682	3829048
36	**Wall Coverings**	2.284	1,484	109333
37	**Synthetic rubber**	2.284	532	37758
38	**Tractors**	2.284	1,368	171019
39	**Vehicles**	1.906	126912	6863115
40	**Textiles**	2.256	84866	2420896
41	**Other Textiles**	1.942	67277	685908
42	**Clothing**	2.137	230662	5015377
43	**Metal and Chemical Machinery**	2.43	421863	6442840

44	**Commercial Machinery**	1.671	70211	2281542
45	**Mining machinery**	2.284	4,756	247552
46	**Other manufacturing**	2.161	282086	7045327

Table 6-2 The Cluster configuration for the UK Manufacturing sector

Table 6-3 to Table 6-6 show a breakdown of the industries within clusters for four of the generated clusters: Cluster 1, Ferrous Metals and Manufacturing, Cluster 22, Paper products, Cluster 30, Chemical and Adhesives, and Cluster 42, Clothing.

Cluster 1	**Ferrous metals and manufacturing**	**WCRi**	**WCRc**
Industry Code	**Industry Name**		
2210	Iron and Steel Industry	0.805	2.227
2220	Steel Tubes	1.041	2.227
2234	Drawing and manufacture of steel wire and steel wire products	1.042	2.227
2235	Other drawing, cold rolling, and cold forming	0.934	2.227
3111	Ferrous metal foundries	1.023	2.227

Table 6-3 Cluster 1 Ferrous metals and manufacturing

Cluster 22	**Paper Products**	**WCRi**	**WCRc**
Industry Code	**Industry Name**		
4722	Household and personal hygiene products of paper	0.805	2.191
4723	Stationary	0.99	2.191
4724	Packaging products of paper and pulp	0.741	2.191
4725	Packaging products of board	1.006	2.191
4728	Other paper and board products	1.035	2.191

Table 6-4 Cluster 22 Paper Products

Cluster 30	**Chemical and Adhesives**	**WCRi**	**WCRc**
Industry Code	**Industry Name**		
2562	Formulated adhesives and sealants	0.896	2.07
2567	Miscellaneous products for industrial use	0.935	2.07
2568	Formulated pesticides	0.756	2.07
2599	Chemical products NES	0.949	2.07

Table 6-5 Cluster 30 Chemical and Adhesives

Cluster 42	**Clothing**	**WCRi**	**WCRc**
Industry Code	**Industry Name**		
4363	Hosiery and other weft knitted goods and fabrics	0.77	2.137
4510	Footwear	0.685	2.137
4532	Men's and boy's tailored outerwear	1.062	2.137
4534	Work clothing and men's and boy's jeans	0.873	2.137
4535	Men's and boy's shirts, underwear and nightwear	0.663	2.137
4536	Women's and girl's light outerwear, lingerie and infants' wear	1.056	2.137
4539	Other dress industries	1.055	2.137

Table 6-6 Cluster 42 Clothing

Algorithm assessed cluster configuration

Now that the original cluster configuration has been calculated, it is possible to evaluate the entire configuration to ensure that industries within the clusters are in fact in the correct clusters. This is done by assessing whether the industries within the clusters are Systematic outliers based upon the industry WCR scores. Those industries that have a low overall WCR_{ic} score in relation to other industries in the cluster could be deemed a Systematic outlier.

The industries' WCR_{ic} score is now assessed against two thresholds: below the 75th percentile value of BCR_i or two standard deviations below the average WCR_{ic} for the industries in the same cluster. Such industries are then reassigned to new clusters where their WCR_{ic} score is relatively higher. One industry was identified as a systematic outlier in Cluster 3: SIC 3640, Aerospace Equipment Manufacturing and Repairing. This industry was moved from Cluster 3, Metal Manufacturing to Cluster 10, Shipbuilding and repairing. After moving this industry out of Cluster 3, the WCR_c for Cluster 3 increases from 1.951 to 2.012, suggesting that this cluster is now a better fit within the cluster configuration than it was in the original configuration.

Cluster 3	**Metal Manufacturing**	**WCRi**	**WCRc**
3142	Metal Doors, Windows etc	0.947	1.951
3162	Cutlery, spoons, forks and similar tableware, razors	0.318	1.951
3164	Packaging products of metal	0.683	1.951
3165	Domestic heating and cooking appliances (non-electrical)	0.465	1.951
3204	Fabricated constructional steelwork	0.956	1.951
3205	Boilers and process plant fabrications	0.881	1.951
3261	Precision chains and other mechanical power transmission equipment	0.911	1.951
3287	Pumps	0.856	1.951
3288	Industrial valves	0.783	1.951
3289	Mechanical, marine and precision engineering NES	0.995	1.951

Table 6-7 Cluster 3 Metal Manufacturing in the algorithm changed cluster configuration

Cluster 10	**Shipbuilding and repairing**	**WCRi**	**WCRc**
3640	Aerospace equipment manufacturing and repairing	0.818	1.355
3610	Shipbuilding and repairing	0.818	1.355

Table 6-8 Cluster 10 Large Transport manufacturing in the algorithm changed cluster configuration

The clusters are also assessed for the presence of Marginal outliers. These outliers are not dependant on the WCR score, but are identified from considering the industries in the clusters and deciding whether those industries would be a better fit in different clusters. These outliers can happen because of limitations within the underlying data. The Marginal outlier may have a relatively high WCR_{ic} score, so therefore would not be detected and moved from the cluster by the algorithm. These industries are moved based upon researcher's own knowledge of the industry.

Table 6-9 below shows an example of a Marginal outlier within a cluster. Cluster A contains four industries three of which involve metal processing, but the fourth is Animal Processing. Due to its WCR score being similar to the others in Cluster A, Animal Processing was not moved by the algorithm to in Cluster B which contain industries that are all more similar to it. This industry, SIC 4126, Animal Byproduct Processing would be moved by the researcher from Cluster A to Cluster B manually and would no longer be classed as a Marginal outlier.

Cluster A SIC code	Industry Name	WCR Score
3142	Metal Doors, Windows etc	1.025
3164	Packaging products of metal	1.045
3288	Industrial valves	1.032
4126	Animal by-product processing	1.068

Cluster B SIC code	Industry Name	WCR Score
4122	Bacon curing and meat processing	1.025
4123	Poultry slaughter and processing	0.987
4116	Processing organic oils and fats	1.002
4115	Margarine and compound cooking fats	0.986

Table 6-9 Example of Marginal Industry within a cluster

After reviewing the cluster configuration, there were no obvious industries that could be classed as Marginal outliers and which needed to be moved from one cluster to another. Table 6-10 below shows the algorithm changed cluster configuration.

Cluster	Cluster name	WCR_c	Number of plants	Total Employment
1	**Ferrous metals and manufacturing**	2.227	47337	2730136
2	**Non-ferrous metal Manufacturing**	2.083	144130	3432349
3	**Metal Manufacturing**	1.951	604429	11816831
4	**Mineral Extraction**	1.817	24751	882671
5	**Other Minerals extraction**	2.284	2759	53638
6	**Mineral Manufacturing**	2.014	135839	2564540
7	**Building Materials**	2.159	74605	1270949
8	**Miscellaneous Manufacturing**	0.845	286521	6752143
9	**Bread and Biscuits**	2.851	124819	3765286
10	**Large Transport Manufacturing**	1.355	78881	5226903
11	**Soaps and Perfumes**	2.517	17863	942793
12	**Grain and Starch**	2.09	4,995	207,010
13	**Pet feeds**	2.599	21219	517638
14	**Leather working**	2.199	27284	359714
15	**Paints**	2.368	20353	708192
16	**Processing of food stuffs**	2.262	24743	1234801
17	**Explosives and ordnance**	1.963	6032	583749
18	**Cooking fats and oils**	1.925	2254	121515
19	**Processing meats**	2.463	37412	2736954
20	**Sugar**	2.284	579	109309
21	**Confectionary**	2.714	57135	2877066
22	**Paper Products**	2.191	78362	2483328
23	**Printing products**	2.388	771320	9434424
24	**Distilling and compounding**	2.284	6575	348332
25	**Brewing and Tobacco**	1.807	19670	1091137
26	**Recreational Manufacturing**	2.228	318502	2319685
27	**Precision Apparatus**	2.187	95291	1978970
28	**Inorganic and organic chemicals**	1.805	22231	1527666
29	**Essential oils**	2.284	2121	86875
30	**Chemical and Adhesives**	2.07	36932	1158463
31	**Man Made Fibre Production**	2.284	1012	152368
32	**Rubber tyres**	2.284	2282	421318
33	**Plastic and rubber products**	2.574	207927	5771510
34	**Electronic Equipment**	2.054	231853	6285035
35	**Wood manufacturing**	2.071	301682	3829048
36	**Wall Coverings**	2.284	1484	109333
37	**Synthetic rubber**	2.284	532	37758
38	**Tractors**	2.284	1368	171019
39	**Vehicles**	1.906	126912	6863115
40	**Textiles**	2.256	84866	2420896
41	**Other Textiles**	1.942	67277	685908
42	**Clothing**	2.137	230662	5015377
43	**Metal and Chemical Machinery**	2.43	421863	6442840
44	**Commercial Machinery**	1.671	70211	2281542
45	**Mining machinery**	2.284	4756	247552
46	**Other manufacturing**	2.161	282086	7045327

Table 6-10 The Algorithm changed Cluster Configuration for the UK Manufacturing Sector

6.4.2 SIC cluster configuration

As there is no definitive set of clusters for the GB manufacturing sector, an alternative is to use SIC codes, either at a two-digit or a three-digit level, to group together industries, so that agglomeration can be analysed. Harris and Moffat (2019) used two digit and three digit SIC codes in their work analysing how spatial proximity and spatial concentration of plants within industries impacts upon productivity.

However, these classifications are based upon product types, unlike the linkages between industries, which are captured when using Delgado's algorithm to generate clusters. This should imply that the Delgado based algorithm generated cluster configuration is a more accurate and appropriate set of clusters than would have been achieved by grouping together industries based solely on product type. To test this, a cluster configuration using the two-digit 1980 SIC will be assessed using Delgado's cluster configuration validation scores.

A cluster configuration will be created by grouping together the two-digit 1980 SIC classifications. This results in 20 clusters (SIC41 and SIC42 have been merged) which correspond to the 20 2-digit classifications, with the largest cluster being the combined SIC codes 41/42 containing 24 four-digit industries, the smallest cluster being the Production of Man-Made Fibres, containing one four-digit industry type. The validations scores are then compared between the three cluster configurations: Original, Algorithm, and SIC 80 2D.

Table 6-11 compares the validation scores of the different types of clusters configurations: the original configuration, the algorithm changed configuration, and the SIC 80 2-digit configuration. The cluster configurations calculated using the Delgado cluster configuration score highest, the validation score for the original is 88.51, and the score for the algorithm changed configuration is 89.00. The configuration made using the SIC 80 2-digit industry configurations has the lowest validation score of the different configurations, 69.60. This suggests that the configurations created using Delgado's method are better at capturing industry linkages, when compared with creating clusters by grouping industry types.

After assessing the different cluster configurations, the algorithm changed configuration has the highest score, which suggests the clusters are meaningfully different, and this method has been best able to capture the linkages between the industries, in comparison with the other configurations. Therefore, the algorithm changed cluster will be used as the Benchmark configuration.

CLUSTER	NUMBER OF CLUSTERS	NUMBER OF INDUSTRY	VS
ALGORITHM	46	175	89.00
ORIGINAL	46	175	88.51
SIC 80 2D	20	175	69.60

Table 6-11 Evaluating the different cluster configurations.

6.4.3 Delgado's Application of the Clustering Algorithm using US Data

The Delgado clustering algorithm was designed using the NAICS classification and the relevant data in the US, so the application of the method to the GB manufacturing sector using the SIC classification system and the available data was not guaranteed to create meaningful clusters.

Delgado uses the NAICS classification system for both goods and services industries. It was introduced into the US in 1997, replacing the SIC system and was developed by the US, Canada and Mexico to standardise the industry types across North America. There have been six editions of the NAICS and Delgado uses the 2007 edition. The 2007 NAICS comprises a granular level of detail, and Delgado uses 6-digit classification.

My work uses the 1980 UK SIC system, which is detailed to a 4-digit level. This is a recognised limitation of this work; furthermore, more modern industries do not have their own classification and are included in older industry classifications which could hide possible inter-industry linkages. Additionally, the more granular industry classification captures more industry linkages, meaning industries are grouped more accurately, when compared with using a more aggregate industry classification.

When comparing the names of the clusters between the US and the UK classifications, as well as looking at the industries within them, there are a lot of similarities. Both UK and US configurations have Apparel/Clothing clusters, Paper Products clusters, and Textile Manufacturing. The UK cluster has more disaggregated clusters such as separating Ferrous and Non-Ferrous metal production. Delgado groups these types of industries together in a single cluster: Upstream Metal Manufacturing. Again, with chemical industries Delgado groups together Inorganic and Organic Chemicals in a cluster together, whereas the UK cluster configuration has separate clusters for these industries. Delgado states that they combined some clusters, after discussion with sectoral experts. Delgado also uses almost 800 industries, both services and goods, whereas the UK configuration uses 207 manufacturing industry classifications. As Delgado states in her work, having too many or two few clusters diminishes the usefulness of the configuration, which may be why some industries have been combined. It may also be the case that some of the inter-industry linkages seem weaker due to using only manufacturing data in the UK configuration. For the 4-digit SIC 1980 classification, while there are some limitations to using older and more aggregated industry classifications, it does not appear to reduce the quality of clusters within the UK cluster configuration.

As a comparison, the clustering algorithm was also applied to 1974-75 Input-Output data for both goods and services industries.[49] The industries within the 1974-75 data are more aggregated compared with the 1980 SIC codes, and the configuration did not have access to the employment co-location and occupational type matrices. The algorithm created a configuration of 22 clusters and comparing it with the Benchmark cluster configuration, the WCR scores are much lower for the individual clusters and for the overall configuration, a score of 68 compared to a score of 89. The lower score could be a result of high level of aggregation of the sectors, which prevents some industry linkages from being captured. The lack of two similarity matrices also prevents industry linkages from being captured, which again lowers the overall configuration score. These are factors that need to be taken into account when using this clustering algorithm.

6.5 Descriptive statistics

Table 6-12 and Table 6-13 show the highest average number of plants and highest average employment in the GB Manufacturing Sector nationally. Cluster 37, Synthetic Rubber has the highest percentage of foreign-owned plants and has the highest number of plants and level of employment, followed by Cluster 3, Metal Manufacturing. There are five clusters which appear in both lists but are in different orders These are Cluster 43, Metal and Chemical Machinery, Cluster 8, Miscellaneous Manufacturing, Cluster 46, Other Manufacturing, Cluster 34, Electronic Equipment, and Cluster 42, Clothing. There are two clusters that only appear in the number of plants rankings, and they are Cluster 26, Recreational Manufacturing and Cluster 35, Wood Manufacturing, and the clusters that appear only in the level of employment rankings are Cluster 39, Vehicles and Cluster 10, Large Transport Manufacturing.

[49] The 1974-75 cluster configuration can be found in Appendix A.10.4

CLUSTER	PERCENTAGE OF PLANTS
23 PRINTING PRODUCTS	15.1%
3 METAL MANUFACTURING	11.8%
43 METAL AND CHEMICAL MACHINERY	8.3%
26 RECREATIONAL MANUFACTURING	6.2%
35 WOOD MANUFACTURING	5.9%
8 MISCELLANEOUS MANUFACTURING	5.6%
46 OTHER MANUFACTURING	5.5%
34 ELECTRONIC EQUIPMENT	4.5%
42 CLOTHING	4.5%
33 PLASTIC AND RUBBER PRODUCTS	4.1%

Table 6-12 Clusters with the highest percentage of plants in the UK

CLUSTER	PERCENTAGE OF EMPLOYMENT
3 METAL MANUFACTURING	10.4%
23 PRINTING PRODUCTS	8.3%
46 OTHER MANUFACTURING	6.2%
39 VEHICLES	6.1%
8 MISCELLANEOUS MANUFACTURING	6.0%
43 METAL AND CHEMICAL MACHINERY	5.7%
34 ELECTRONIC EQUIPMENT	5.5%
33 PLASTIC AND RUBBER PRODUCTS	5.1%
42 CLOTHING	4.4%
35 WOOD MANUFACTURING	3.4%

Table 6-13 Clusters with the highest percentage of employment in the UK

Looking at the ownership levels, the clusters with the highest percentage foreign-owned plants can be found in Table 6-14, and the clusters with the highest percentage of employment in foreign-owned plants can be found in Table 6-15. The clusters with the highest percentage of foreign-owned plants are Clusters 46, Other Manufacturing, Cluster 23, Printing Products, and Cluster 3, Metal Manufacturing. The most EU- and US-owned plants are in Cluster 46, Other Manufacturing while the most ROW-owned plants are based in Cluster 7, Building Materials.

In terms of employment, the highest levels of foreign-owned employment are in Cluster 39, Vehicles, Cluster 46, Other Manufacturing, and Cluster 34, Electronic Equipment. The cluster with he highest percentage employment from EU-, US-, and ROW-owned investment is Cluster 3, Vehicles.

CLUSTER	PERCENTAGE OF FO PLANTS
37 SYNTHETIC RUBBER	34.4%
32 RUBBER TYRES	22.7%
24 DISTILLING AND COMPOUNDING	19.7%
15 PAINTS	19.1%
28 INORGANIC AND ORGANIC CHEMICALS	14.2%
29 ESSENTIAL OILS	14.1%
31 MAN MADE FIBRE PRODUCTION	13.9%
30 CHEMICAL AND ADHESIVES	13.8%
7 BUILDING MATERIALS	11.6%
38 TRACTORS	11.1%

Table 6-14 Clusters with the highest percentage of FO plants

CLUSTER	PERCENTAGE OF FO EMPLOYMENT
32 RUBBER TYRES	77%
38 TRACTORS	72%
37 SYNTHETIC RUBBER	72%
39 VEHICLES	46%
30 CHEMICAL AND ADHESIVES	38%
29 ESSENTIAL OILS	34%
11 SOAPS AND PERFUMES	33%
15 PAINTS	33%
21 CONFECTIONARY	32%
44 COMMERCIAL MACHINERY	32%

Table 6-15 Clusters with the highest percentage of employment in FO plants

Table 6-16 and Table 6-17 use the Benchmark configuration and show how the number of plants and level of employment within the clusters change over three time periods. The time periods cover ten years each: 1984-1993, 1994-2003, and 2004-2014. Table 6.17 shows the top ten clusters in terms of number of plants nationally over three decades. The top two clusters remain the same across the three decades, Cluster 23, Printing Products and Cluster 3, Metal Manufacturing. While the third largest cluster changes from Cluster 43, Metal and Chemical Machinery to Cluster 46, Other Manufacturing between 2004 and 2014. There are other changes, Cluster 42, Clothing had the fourth highest number of plants between 1984-1993, this then dropped to eighth between 1994-2003 and disappeared from the top ten between 2004 and 2014, being replaced by Cluster 6, Mineral Manufacturing. Cluster 35, Wood Manufacturing, Cluster 26, Recreational Manufacturing and Cluster 8, Miscellaneous Manufacturing fluctuated between fifth and seventh place across the three decades.

In terms of employment, Cluster 3, Metal Manufacturing has the highest total employment nationally across the three decades, followed by Cluster 23, Printing Products. Cluster 42, Clothing moved from third highest level of employment in 1984-1993 to ninth in 1994-2003, before dropping out of the top ten by 2004-2014. Cluster 8, Miscellaneous Manufacturing rose from eighth place between 184-1993, to third place between 2004-2014.

1984-1993	1994-2003	2004-2014
23 Printing Products	23 Printing Products	23 Printing Products
3 Metal Manufacturing	3 Metal Manufacturing	3 Metal Manufacturing
43 Metal and Chemical Machinery	43 Metal and Chemical Machinery	46 Other Manufacturing
42 Clothing	26 Recreational Manufacturing	43 Metal and Chemical Machinery
35 Wood Manufacturing	35 Wood Manufacturing	8 Miscellaneous Manufacturing
26 Recreational Manufacturing	8 Miscellaneous Manufacturing	35 Wood Manufacturing
8 Miscellaneous Manufacturing	46 Other Manufacturing	26 Recreational Manufacturing
34 Electronic Equipment	42 Clothing	34 Electronic Equipment
33 Plastic and Rubber Products	34 Electronic Equipment	33 Plastic and Rubber Products
2 Non-ferrous Metal Manufacturing	33 Plastic and Rubber Products	6 Mineral Manufacturing

Table 6-16 The clusters with the highest number of plants over time

1984-1993	1994-2003	2004-2014
3 Metal Manufacturing	3 Metal Manufacturing	3 Metal Manufacturing
23 Printing Products	23 Printing Products	23 Printing Products
42 Clothing	46 Other Manufacturing	8 Miscellaneous Manufacturing
46 Other Manufacturing	39 Vehicles	33 Plastic and Rubber Products
43 Metal and Chemical Machinery	8 Miscellaneous Manufacturing	46 Other Manufacturing
39 Vehicles	34 Electronic Equipment	39 Vehicles
34 Electronic Equipment	43 Metal and Chemical Machinery	43 Metal and Chemical Machinery
8 Miscellaneous Manufacturing	33 Plastic and Rubber Products	34 Electronic Equipment
33 Plastic and Rubber Products	42 Clothing	35 Wood Manufacturing
9 Bread and Biscuits	35 Wood Manufacturing	9 Bread and Biscuits

Table 6-17 The clusters with the highest level of employment over time

6.5.1 North East descriptive statistics

Table 6-18 shows the clusters with the highest percentage of plants in the North East of England. Cluster 3, Metal Manufacturing has the highest number percentage of plants, differing from the national figure, where Cluster 37, Synthetic Rubber has the highest percentage of plants. The North East top clusters by number of plants differs from the national picture, with fewer rubber and chemical based clusters and more foodstuffs and vehicle based clusters.

Table 6-19 shows the cluster with the highest percentage of employment is also Cluster 3, Metal Manufacturing accounting for 10% of employment. This again differs from the national figure, where Cluster 32, Rubber Tyres has the highest percentage of employment. This is followed by Cluster 9, Bread and Biscuits which accounts for 7.2% of employment. Most of the employment in the North East is based in the clusters with industries that have traditionally been based in the region such as the plastic and chemical clusters as well as metal manufacturing and ferrous metal clusters.

In terms of foreign ownership, Table 6-20 shows the number of clusters with highest percentage of foreign-owned plants in the North East. The cluster with the highest percentage of foreign-owned plants in the North East is Cluster 15, Paints, followed by Cluster 28, Inorganic and Organic Chemicals and Cluster 30, Chemicals and Adhesives. Compared with the national picture, all three of these clusters appear in the top ten. However, on a national level a greater percentage of foreign-owned plants are in Cluster 37, Synthetic Rubber and Cluster 32, Rubber Tyres. Neither of these clusters appear in the top ten for highest percentage of foreign-owned plants in the North East. The greatest number of EU- owned plants are in Cluster 33, Plastic and Rubber Products, most US-owned plants are in Cluster 43, Metal and Chemical Machinery, and most ROW-plants are in Cluster 39, Vehicles.

CLUSTER	TOTAL
3 METAL MANUFACTURING	14.0%
23 PRINTING PRODUCTS	10.4%
43 METAL AND CHEMICAL MACHINERY	8.0%
35 WOOD MANUFACTURING	6.6%
8 MISCELLANEOUS MANUFACTURING	6.1%
26 RECREATIONAL MANUFACTURING	5.5%
33 PLASTIC AND RUBBER PRODUCTS	5.3%
46 OTHER MANUFACTURING	4.9%
34 ELECTRONIC EQUIPMENT	4.8%
9 BREAD AND BISCUITS	4.4%

Table 6-18 Clusters with the highest percentage of plants in the North East

CLUSTER	PERCENTAGE OF EMPLOYMENT
3 METAL MANUFACTRING	10.0%
39 VEHICLES	7.2%
34 ELECTRONIC EQUIPMENT	7.2%
8 MISCELLANOUS MANUFACTRUING	6.8%
33 PLASTIC AND RUBBER PRODUCTS	6.2%
43 METAL AND CHEMICAL MACHINARY	5.1%
28 INORGANIC AND ORGANIC CHEMICALS	4.9%
23 PRINTING PRODUCTS	4.6%
46 OTHER MANUFACTURING	4.3%
1 FERROUS METALS AND MANUFACTURING	4.3%

Table 6-19 Clusters with the highest average of employment in North East

Table 6-21 shows the clusters with the highest percentage of foreign-owned employment. The cluster with the highest percentage of employment is Cluster 39, Vehicles, whereas nationally it is Cluster 32, Rubber Tyres. There are some differences, Cluster 19, Processed Meats, Cluster 33, Plastics and Rubber, Cluster 8, Miscellaneous Manufacturing, Cluster 34, Electronic Equipment, and Cluster 6, Mineral Manufacturing appear in the North East top ten but not national top ten. The cluster with the highest EU employment is Cluster 34, Electronic Equipment, the highest US and ROW employment is in Cluster 39, Vehicles.

CLUSTER	PERCENTAGE OF FO PLANTS
15 PAINTS	21.8%
28 INORGANIC AND ORGANIC CHEMICALS	20.7%
30 CHEMICAL AND ADHESIVES	16.9%
11 SOAPS AND PERFUMES	15.0%
39 VEHICLES	13.9%
22 PAPER PRODUCTS	9.5%
7 BUILDING MATERIALS	8.5%
33 PLASTIC AND RUBBER PRODUCTS	8.1%
34 ELECTRONIC EQUIPMENT	7.9%
6 MINERAL MANUFACTURING	7.5%

Table 6-20 The clusters with the highest percentage of FO plants in the North East

CLUSTER	PERCENTAGE OF FO EMPLOYMENT
39 VEHICLES	72.3%
11 SOAPS AND PERFUMES	71.6%
15 PAINTS	36.7%
44 COMMERCIAL MACHINERY	35.3%
19 PROCESSING MEATS	35.3%
30 CHEMICAL AND ADHESIVES	30.4%
33 PLASTIC AND RUBBER PRODUCTS	29.2%
8 MISCELLANEOUS MANUFACTURING	28.9%
6 MINERAL MANUFACTURING	28.2%
34 ELECTRONIC EQUIPMENT	26.6%

Table 6-21 The clusters with the highest percentage of FO employment in the North East

Examining the change of cluster ranking over time in the North East, Table 6-22 shows the highest number of plants are in Clusters 3, Metal Manufacturing, Cluster 23, Printing Products, and Cluster 43, Metal and Chemical Machinery across all time periods. As a region that has previously supported heavy industries, having these three clusters at the top for the number of plants is not unexpected. There are numerous supply chains feeding into larger manufacturing plants, such as the Nissan factory in Sunderland. Cluster 9, Bread and Biscuits and Cluster 42, Clothing are in the top ten clusters in the first period, but by 2004-2014, they have dropped out of the top ten. Cluster 46, Other Manufacturing and Cluster 6, Mineral Manufacturing replacing these clusters in the final period.

1984-1993	1994-2003	2004-2014
3 Metal Manufacturing	3 Metal Manufacturing	3 Metal Manufacturing
23 Printing Products	23 Printing Products	23 Printing Products
43 Metal and Chemical Machinery	43 Metal and Chemical Machinery	43 Metal and Chemical Machinery
35 Wood Manufacturing	26 Recreational Manufacturing	8 Miscellaneous Manufacturing
8 Miscellaneous Manufacturing	35 Wood Manufacturing	46 Other Manufacturing
9 Bread and Biscuits	33 Plastic and Rubber Products	35 Wood Manufacturing
26 Recreational Manufacturing	8 Miscellaneous Manufacturing	33 Plastic and Rubber Products
34 Electronic Equipment	9 Bread and Biscuits	34 Electronic Equipment
33 Plastic and Rubber Products	46 Other Manufacturing	26 Recreational Manufacturing
42 Clothing	34 Electronic Equipment	6 Mineral Manufacturing

Table 6-22 The cluster with the highest number of plants over time in the North East of England

In terms of total employment, Table 6-23 shows the cluster with the highest employment is Cluster 3, Metal Manufacturing, with the second highest employment in Cluster 34, Electronic Equipment between 1984-1993, and then Cluster 39, Vehicles from 1994 onwards. With the expansion of the Nissan factory in Sunderland, this is not unexpected. It is a large employer for the North East of

England and is supplied by many local plants. Cluster 39, Vehicles does not appear at the top in terms of number of plants, as these large plants dominate the region in terms of employment, but not in terms of number of plants, Nissan having, for example, a single large plant. Cluster 42, Clothing, Cluster 10, Large Transport Machinery, and Cluster 28, Inorganic and Organic Chemicals are the in the top ten clusters during the first period, but by 2004-2014 have dropped out of the top ten and have been replaced by Cluster 23, Printing Products, Cluster 46, Other Manufacturing, and Cluster 35, Wood Manufacturing.

1984-1993	**1994-2003**	**2004-2014**
3 Metal Manufacturing	3 Metal Manufacturing	3 Metal Manufacturing
34 Electronic Equipment	39 Vehicles	39 Vehicles
28 Inorganic and Organic Chemicals	34 Electronic Equipment	8 Miscellaneous Manufacturing
42 Clothing	33 Plastic and Rubber Products	33 Plastic and Rubber Products
8 Miscellaneous Manufacturing	8 Miscellaneous Manufacturing	43 Metal and Chemical Machinery
1 Ferrous Metals and Manufacturing	43 Metal and Chemical Machinery	23 Printing Products
33 Plastic and Rubber Products	46 Other Manufacturing	34 Electronic Equipment
9 Bread and Biscuits	23 Printing Products	35 Wood Manufacturing
10 Large Transport Manufacturing	1 Ferrous Metals and Manufacturing	46 Other Manufacturing
43 Metal and Chemical Machinery	42 Clothing	1 Ferrous Metals and Manufacturing

Table 6-23 The clusters with the highest level of employment over time in the North East of England

6.5.2 Location quotients of clusters based in the North East of England

While Cluster 3, Metal Manufacturing, Cluster 23, Printing Products and Cluster 43, Metal and Chemical Machinery are the top clusters in the North East based upon the number of plants, this does not show how the presence of these clusters compares with the national average. This can be done however by examining the top ten clusters location quotients (LQ), which is a method that can assess a regions' specialisation relative to the national average.

There have been external studies that have identified clusters of industries in the North East. The North East of England Process Industry Cluster (NEPIC) was developed in 2004 by the UK Government. It is an economic cluster created using Porters' clustering theories across the chemical process sector. It includes seven industries as well as supply chain companies. The industries are Pharmaceuticals, Petrochemicals, Fine and Speciality Chemical, Biosciences, Biotechnology, Polymers and Rubber, and Commodity Chemicals. It is now also including Net-Zero industries as that sector expands.

The Industrial Decarbonisation Research and Innovation Centre identified the Teesside Industrial Cluster which is made up of seven industries: Chemicals and Process, Steel, Biofuels, Pharmaceutical, Oil and Gas, Mining, and Renewable power. While the North East Local Enterprise Partnership (LEP)[50] identified four key sectors: Advanced Manufacturing, Digital, Energy, and Health and Life Sciences.

Location Quotients are ratios that compare the regional concentration of an industry or cluster with that observed in a larger areal unit, usually nationally (Wheeler, 2005). It is a simple and useful tool that allows for identifying where a region specialises in certain clusters. It is useful when trying to identify regional economies. There are more data intensive approaches which can be used when trying to identify if a region benefits from localisation economies, but the Location Quotients are a simpler approach that provide some descriptive statistics on regional concentration. The Location Quotients can be calculated by using the percentage of a regional descriptor (normally employment) within an industry or cluster, divided by the national percentage of the descriptor within an industry or cluster (McMillen, 2005). For this work, LQs have been calculated in terms of plants and then the total employment within the same cluster. The LQs for the North East will be calculated for the number of plants and level of employment for the whole data set, 1984-2014, using the equation below.

$$LQ_c = \frac{Percentage\ of\ regional\ descriptor\ in\ cluster\ c}{National\ percentage\ of\ descriptor\ in\ cluster\ c} \qquad (6.2)$$

Equation 6-2 Location Quotients equation

In the North East, there is a higher concentration of plants in Cluster 45, Mining Machinery, Cluster 28, Inorganic and Organic Chemicals, and Cluster 5, Other Minerals Extraction when compared with the national average concentration. In terms of employment, the cluster with the highest LQ score is Cluster 5, Other Minerals Extraction, followed by Cluster 28, Inorganic and Organic Chemicals, and then Cluster 45, Mining Machinery.

When comparing the clusters within the benchmark configuration with the clusters from external studies, there are some overlaps. In terms of North East specialisation, in both the number of plants and level of employment, Cluster 28, Inorganic and Organic Chemicals, Cluster 31, Man Made Fibres Production, and Cluster 1, Ferrous Metals and Manufacturing are similar to the clusters identified in the external studies. Clusters overlapping with external clusters in terms of the number of plants are Cluster 30, Chemical and Adhesives, Cluster 31, Man Made Fibres Production, and Cluster 32, Rubber Tyres. Because the sectors in the external studies are quite broad there may be some overlaps with

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[50] A local enterprise partnership that focuses promoting and developing growth in local authority areas of County Durham, Gateshead, Newcastle, North Tyneside, Northumberland, South Tyneside, and Sunderland.

the benchmark configuration, such as Cluster 15, Paints and Cluster 17, Explosives and Ordnance in terms of employment, however it is difficult to be certain.

The North East has an above national average specialisation in Cluster 28, Inorganic and Organic Chemicals, which has been identified by the external North East studies. There are two clusters, Cluster 45, Mining Machinery and Cluster 5, Other Minerals Extraction, where the North East has regional specialisation for both the number of plants and level of employment respectively. Crucially, these clusters have not previously been identified as significant in the external literature, possibly because the literature is focusing on specific sectors. The clusters previously defined in former studies and those set up by local and governmental bodies seem to have been focused on, and driven by, certain limited sectors, such as the NEPIC economic cluster being based on chemical processes. There has been no objective assessment of all industry linkages to establish clusters, and the emergence of mining related activities as economically significant in the region is a validation of such an assessment in this thesis.

CLUSTER	LQ PLANTS	CLUSTER	LQ EMPLOYMENT
45 MINING MACHINERY	2.429	**5 OTHER MINERALS EXTRACTION**	8.684
28 INORGANIC AND ORGANIC CHEMICALS	2.230	**28 INORGANIC AND ORGANIC CHEMICALS**	3.563
5 OTHER MINERALS EXTRACTION	1.953	**45 MINING MACHINERY**	1.912
36 WALL COVERINGS	1.839	**1 FERROUS METALS AND MANUFACTURING**	1.869
9 BREAD AND BISCUITS	1.773	**10 LARGE TRANSPORT MANUFACTURING**	1.830
32 RUBBER TYRES	1.668	**17 EXPLOSIVES AND ORDNANCE**	1.805
31 MAN MADE FIBRES PRODUCTION	1.631	**15 PAINTS**	1.705
1 FERROUS METALS AND MANUFACTURING	1.427	**31 MAN MADE FIBRES PRODUCTION**	1.647
30 CHEMICAL AND ADHESIVES	1.394	**25 BREWING AND TOBACCO**	1.521
7 BUILDING MATERIALS	1.359	**36 WALL COVERINGS**	1.457

Table 6-24 Location Quotients for the number of plants and level of employment in the top 10 North East clusters

Table 6-25 below contains the top ten clusters by level of employment in the North East of England with their LQ scores. Most of the clusters in the top ten have a level of concentration higher than the national average. Cluster 28, Inorganic and Organic Chemicals has an LQ score of 3.563, and Cluster 1, Ferrous Metals and Manufacturing with a LQ score of 1.869 are the two clusters that appear in the top ten cluster in terms of total level of employment and top ten employment LQ scores. There are four clusters that have an above average LQ scores: Cluster 39, Vehicles, Cluster 34, Electronic Equipment, Cluster 8, Miscellaneous Manufacturing and Cluster 33, Plastic and Rubber Products. There are four clusters that are below the national average in terms of employment: Cluster 3, Metal Manufacturing, Cluster 43, Metal and Chemical Machinery, Cluster 23, Printing Products, and Cluster 42, Clothing.

CLUSTER	LQ
3 METAL MANUFACTURING	0.992
39 VEHICLES	1.141
34 ELECTRONIC EQUIPMENT	1.243
8 MISCELLANEOUS MANUFACTURING	1.092
33 PLASTIC AND RUBBER PRODUCTS	1.171
43 METAL AND CHEMICAL MACHINERY	0.867
28 INORGANIC AND ORGANIC CHEMICALS	3.563
23 PRINTING PRODUCTS	0.563
1 FERROUS METALS AND MANUFACTURING	1.869
42 CLOTHING	0.955

Table 6-25 Location Quotients for the top ten clusters in terms of employment

Regional differences

Separating foreign ownership into the different ownership groups, found that an increase in the presence of both EU- and US-owned plants had a positive, but insignificant impact on productivity in the UK-owned plants within the same cluster. The impact of ROW-owned plants was found to be negative, but again, insignificant. When including the industrial area dummy variables for Sunderland, Middlesbrough and Newcastle in the model, the impact of the presence of EU-owned plants within a cluster became negative, but still insignificant.

The most important clusters for the North East regional economy by employment were Cluster 3, Metal Manufacturing, Cluster 39, Vehicles, and Cluster 34, Electronic Equipment. When importance to the regional economy is assessed by Clusters with the highest number of plants, Cluster 3, Metal Manufacturing, continues to be important and this appears to be both widespread and a high employer regionally and nationally. Cluster 23, Printing Products and Cluster 43, Metal and Chemical Machinery also feature as widespread businesses. This could imply many smaller plants in these clusters with potential inefficiencies, or that the industries are widespread indicators of thriving small and medium enterprises in these areas.

The clusters with an above national average representation in the North East by both employment and number of plants are Cluster 5, Other Minerals Extraction, reflecting exploitation of the mineral based geology of the region. It is likely that this supports the above national average representation in terms of employment of Cluster 45, Mining Machinery. Cluster 28, Inorganic and Organic Chemicals also has above national average representation although is already widely recognised.

In the North of England region, the Clusters with the highest numbers of plants are Cluster 3, Metal Manufacturing, Cluster 23, Printing Products, and Cluster 43, Metal and Chemical Machinery, and in terms of employment Cluster 3, Metal Manufacturing, Cluster 8, Miscellaneous Manufacturing and Cluster 23, Printing Products. Cluster 3, Metal Manufacturing appears to be an important industry nationally, as it also features in the South East as a Cluster with a high number of plants, although not as a high employer there, which suggests increased mechanisation and potentially improved productivity from these plants. Across the North it is significant in terms of numbers of plants and employment levels. The remaining Cluster 23, Printing Products and Cluster 43, Metal and Chemical Machinery, important in the North of England region do not parallel industries most important to the North East, as there is no refence to vehicles, chemicals or mining related activities. This suggests that including the North East in a broader industrial strategy devised to cover the North of England as a whole, would significantly risk failing to support vital North East requirements.

The most important Clusters in the South East ordered by number of plants are Cluster 23, Printing Products, Cluster 3, Metal Manufacturing and Cluster 43, Metal and Chemical Machinery, and when ordered by level of employment Cluster 23, Printing Products, Cluster 8, Miscellaneous Manufacturing and Cluster 34, Electronic Equipment. Cluster 34, Electronic Equipment is a significant employer across both the South East and the North East suggesting investment in this area nationally would benefit both regions.

Differences in regional economies become most apparent when the Clusters are ordered by above national average representation in the three comparison regions. The Clusters which have an above national average number of plants in the North of England include Cluster 36, Wall Coverings, Cluster 31, Man Made Fibre Production, Cluster 40, Textiles, none of which are significant in the North East region. In terms of above national average employment levels, within the North of England Cluster 36, Wall Coverings, Cluster 28, Inorganic and Organic Chemicals, Cluster 40, Textiles are most significant. Their relevance to the North East is minimal and strongly suggests the North East requires its own industrial strategies reflecting its priorities and supporting its unique industrial base.

In the South East the Clusters with an above national average number of plants are Cluster 10, Large Transport Manufacturing, Cluster 27, Precision Apparatus, Cluster 29, Essential Oils, widely divergent from the industries most relevant to North East prosperity. Cluster 27, Precision Apparatus may reflect the higher level of R&D located there. When measured by above national average levels of employment, Cluster 37, Synthetic Rubber, Cluster 29, Essential Oils, and Cluster 27, Precision Apparatus are most important in the South East, which broadly reflects the most significant Clusters by plant number and further reinforces the wide differential between the most significant industries for the South East region when compared with both the North and the North East.

6.6 Limitations

The method used to calculate the clusters in this thesis was selected because it overcomes some of the limitations seen with other clustering configurations. It provides a single definition of clusters that can be compared across regions. Previous methodologies have created clusters based upon individual areas of research and specific parts of economy, making it very difficult to compare results from different studies or cluster configurations across the regions. Nevertheless, while this methodology overcomes these issues, when applying the methodology to UK data, it is not itself without some limitations.

Firstly, the lack of the similarity matrices available for the UK data limits the inter-industry linkages that can be exploited to establish connections. In future research, it would be useful to look into the available data for the UK and establish if the cluster configuration could be adapted to include these data types.

Secondly, there is no weighting of the matrices; each one is weighted equally in the creation of the cluster configuration. The linkages in some matrices may be more important to the creation of clusters than others. Without weighting the matrices, those linkages which are not as important are given the same level of importance as those linkages which are highly significant. The clusters created in this chapter are reasonable, yet there are some instances where the industries do not appear to link together in cluster, Cluster 8, Miscellaneous Manufacturing is a good example of this, although by definition this is likely to lack coherence. It may be useful to examine the possibility of weighting certain matrices to see if improvements in the cluster classification can be made.

6.7 Conclusion

This chapter constructs a cluster configuration for the UK manufacturing sectors based on the Delgado et al (2016) clustering method. It uses a combination of matrices based upon employment, establishment, Input-Output, and Occupational data to form a series of cluster configurations that are then evaluated. Most cluster configurations in the UK have been created using either high level industry groupings or clusters created using the researchers' interests, or available funding streams, as the justification for the configuration (DePropris & Driffield, 2005). The numerous methods being used to create clusters makes comparison difficult across the different sets of clusters (Bergman & Feser, 2020) and can overlook less high profile or more poorly funded areas.

For the UK manufacturing industry, using the 1980 SIC system and 29 similarity matrices, the best cluster configuration is achieved using the Validation Score evaluation method developed by Delgado, the Cluster Configuration using LC-Emp-LC-Est-IO, with 46 clusters. Compared to industry groupings, the method normally used to create clusters of industries, the Validation Score for the cluster configuration is greater, suggesting that it is a better representation of inter-industry linkages than simple industry groupings.

The cluster configuration generated in this thesis identified that the North East region differs significantly in terms of cluster representation regarding employment and plant levels from the wider North of England and the South East regions. It would appear that Cluster 3, Metal Manufacturing is a significant activity across all regions studied, and therefore potentially nationally. In all other respects, the North East region has its own unique cluster make up, specifically including mining related activities and vehicles in addition to the well-recognised chemical industries.

Limitations with this method mainly stem from the quality of data inputted into the algorithm, as well as the availability of the data which can be used to create the cluster definition matrices. A difficulty in using this method is ensuring that the data is sufficiently granular to capture inter-industry linkages, to ensure that the clusters are meaningful. This can be seen when comparing the US Cluster configuration, UK Manufacturing configuration and the Early Configuration.

The US cluster configuration uses very granular industry classifications for both goods and services, which enables very detailed clusters and cluster configurations. For the UK Manufacturing configuration, most of the clusters are meaningful; there are two that score low on the WCR score, but this could be due to using the 4-Digit 1980 SIC system, which is not able to capture the same level of linkages as the 6-Digit 2007 NAISC system. For the Early Configuration, the industry classification is very aggregated, and most of the cluster scores are very low when compared to the UK manufacturing configuration. This configuration also uses only four out of the five cluster definition matrices that the UK Manufacturing Configuration uses.

Now that the cluster configuration has been defined, it will be used to examine how the presence of foreign-owned plants impact on domestically-owned plants' productivity w the same cluster.

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7. The impact of the spatial concentration of foreign-owned plants on UK-owned plant within clusters of industries in the North East of England

7.1 Introduction

Chapter 5 showed the influence of ownership on productivity within plants, but it did not show the way in which foreign-owned plants impact, through spillovers, on the productivity within UK-owned plants. From a Governmental perspective, one of the main attractions of FDI is the potential for the more productive foreign-owned plants recruited into a region to pass on their technological advantages to the UK-owned plants. Previous work by Driffield and Love (2007), as noted in Chapter 3, found there are scenarios where FDI can have a negative impact upon domestically-owned plants, Dunning (1977, 1988), Javorcik (2004) and Castellani et al (2024) finding an absence of positive spillovers, potentially due MNE's withholding their ownership advantages.

This chapter examines how the presence of foreign-owned plants in the North East has an impact on productivity within UK-owned plants. Examining the impact of the spatial concentration of foreign-owned plants, using cluster rather than industry classifications captures the inter-industry linkages that are lost by simply using the intra-industry classifications. For this, the spatial concentration of foreign-owned plants will be calculated within the cluster configuration established in the previous chapter. The spatial concentration of foreign-owned plants will be calculated in relation to UK-owned plants within the same cluster using the Scholl and Brenner (2016) spatial concentration index.

The chapter order is as follows: section 7.2 section presents the methodology for the Scholl and Brenner (2016) index, section 7.3 presents the methodology used to estimate the impact of spatial concentration of foreign-owned plants on productivity, section 7.4 presents the results, and section 7.5 concludes the chapter.

7.2 Establishing Spatial Concentration

There are several methods that can be used to construct measures of the spatial concentration of plants, often with the aim of detecting the existence of clusters. Porter (2003) and Ellison and Glaeser (1997) developed methods to estimate spatial concentration dependent upon user defined regional boundaries. Porter's method is very simple, with some arguing that it is too simple, in detecting the presence of clusters, and illustrates a region's trend towards industry specialisation (Woodward et al., 2009). Ellison and Glaeser's (1997) method (denoted EG hereafter) is more advanced as it includes additional industry methods and detects 'random' as well as additional agglomerations. Like Porter, however, this index indicates a region's level of specialisation rather than the presence of clusters (Duranton & Overman, 2005).

The main disadvantage with these models is that they use predetermined administrative boundaries, rather than economic boundaries. De Propris and Driffield (2005) for example, used the travel-to-work-areas (TTWAs) as their region when they examined FDI spillovers in relation to the cluster development in the UK. The TTWA regional boundary more accurately reflects economic flows, when compared with administrative boundaries such as postcodes and Local Authority areas.

An issue with using locational boundaries or single-distance intervals,[51] as in the studies above, is that these do not take into account units/plants located close to any boundary, which could have an impact on other postcodes or Local Authorities adjoining the boundary. Openshaw (1984) coined the term "modifiable areal unit problem" (MAUP). MAUPs can be spilt into two categories. One is when a user moves between different levels of aggregation, such as when analysis moves from a region to a county, then to state. This is known as the 'scaling problem' of the MAUP. Each of these aggregations will produce a different index, dependent upon which industries are present in those areas and there is no way to test which of these levels is the best representation of clusters. This can be seen in the EG index when moving between levels of aggregation resulting in a variation of clusters.

The second is where boundaries are drawn which also have an impact upon the results. The borders of regions are not necessarily based upon economic structures and are usually administrative, referred to as the 'zoning problem' of the MAUP. These could be firms and plants economically related, but which straddle an administrative boundary. The external plants may impact upon those firms within

[51] Single distance intervals use a set distance from a randomly selected starting point, with other points at a set distance interval away from the randomly selected starting point McGrew Jr, J. C., & Lembo Jr, A. J. (2023). *An introduction to statistical problem solving in geography* (Vol. 4). Waveland Press.

the boundary area, but which are excluded from the analysis due to the location of the boundary line. A method needs to be used that is economically focused, not based on regional administrative boundaries.

7.2.1 The Spatial concentration index

To overcome the MAUP, the Spatial Concentration Index proposed by Scholl and Brenner (2016), can be used. This technique does not focus on single-distance intervals, as previous distance-based methods do, but on the spatial concentration of firms, and is able to overcome the 'modifiable real unit problem' (MAUP) as regional or city boundaries are not used (Scholl & Brenner 2016). This method calculates plant-specific values of concentration, denoted as D_{it}, by summing the inverted distances of one firm to all other firms.

The formula below shows how the D_{it} values are calculated:

$$D_i = \frac{1}{J-1}\sum_{j=1, j\neq i}^{J}(f(d_{i,j}))^{-1} \tag{7.1}$$

Equation 7-1 Di value formula

The term $(f(d_{i,j}))^{-1}$ represents an inverted function of the distance between two points, such as two plants. A high value of D indicates a higher spatial concentration. The D will converge to zero as the distance from the initial point increases. To ensure that this index is comparable across industries, an average is taken of the number of observations *J*. The term $\frac{1}{J-1}$ ensures that the index is independent of the number of firms or plants in a certain industry Distance functions

The value of D is also impacted upon by the type of distance function the user decides to use to compute said values. Scholl and Brenner (2016) present two distance function options: a hyperbola function $(d_{i,j})^{-1}$ and a negative exponential function $e^{-\alpha d_{i,j}}$.

The hyperbola function is the more intuitive of the two, however it does have a problem with short distances. If there are two firms/plants very close to each other, for example if they share the same building, this will result in infinite D values. To overcome this problem, a threshold of 1km has been introduced. The means that those plants/firms located within this threshold will be given the value that is the same for both hyperbola and negative exponential function. The hyperbola function formula now becomes:

$$D_i = \frac{1}{J-1}\sum_{j=1, j\neq i}^{J}\frac{1}{max\{1\ km, d_{i,j}\}} \tag{7.2}$$

Equation 7-2 Hyperbola function

Figure 7-1 below is a visual example on how these D values are calculated:

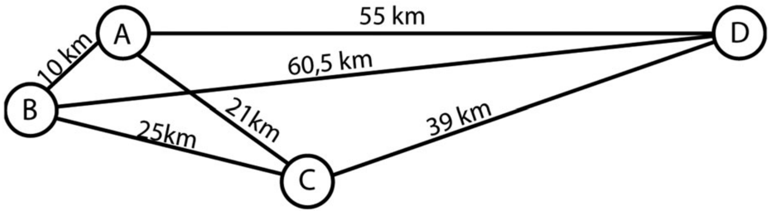

Figure 7-1 Di value distance diagram (Scholl and Brenner 2016)

To calculate the D value for plant A, for example, the equation with the inverted distances calculated would be:

$$\frac{1}{3} \cdot \left(\frac{1}{10km} + \frac{1}{21km} + \frac{1}{55km}\right) = 0.055 \left[\frac{1}{km}\right] \quad (7.3)$$

Equation 7-3 Example D_i hyperbola function

The D value for plant A with these three other plants would be 0.055.

The negative exponential function does not require a threshold value, as for small distances it converges to 1. There is a distance decay factor, α, present. For small distances, this factor will cause the function to produce values around one, and for larger distances, it will result in values close to zero. To control for given distances' contribution to the spatial concentration index, a value for α is chosen, in this case it is -0.05. This will result in the results being comparable with the hyperbola function. This function has a short value range compared to the hyperbola function. While it is not restricted by thresholds, it does have the potential to produce more extreme values. The introduction of the negative exponential function results in:

$$D_i = \frac{1}{J-1} \sum_{j=1, j\neq i}^{J} e^{-0.05(d_{i,j})} \quad (7.4)$$

Equation 7-4 Negative exponential function

It is also possible to include a weight for each firm, which is based upon the firms' share of employment. When including the employment weight in the function it now becomes:

$$D_i = \sum_{j=1, j\neq i}^{J} \left(\frac{\sum_{k=1, k\neq i} E_k}{E_j} f\left(d_{i,j}\right)\right)^{-1} \quad (7.5)$$

Equation 7-5 D_i value function with weight of employment share

Where $\sum_{k=1,k\neq i} E_k$ is the total employment for all other firms except firm *i* in the cluster and E_j is the number of employees in firm *j*.

7.2.2 *Spatial configurations around foreign-owned plants*

This metric can give insight into the spatial concentration of plants without the use of predetermined boundaries. The index is also not affected by the size of area that is being used to calculate spatial concentration.

In their original work, Scholl and Brenner (2016) used the method to identify the presence of clusters in the German micro-technology industry, across Germany, based upon the level of spatial concentration. As I have already defined clusters, using the Delgado algorithm, I can use the Spatial Concentration Index within these clusters to establish the concentration of plants, based upon other plant characteristics, such as ownership. For this work, the D values will be used to calculate the spatial concentration of foreign-owned plants in relation to UK-owned plants in the same cluster.

To begin with, D values will be calculated using employment weights and the negative exponential function between UK-owned plants and foreign-owned plants within the same cluster, as this method is better over smaller distances (Scholl and Brenner, 2016). To overcome MAUP, D values are calculated for UK-owned plants using every region in the UK.[52] The next step will be to examine whether an increase in the spatial concentration of certain ownership types impacts upon the productivity of UK-owned plants in the same cluster. D values will be calculated between UK-owned plants and foreign ownership, and between UK-owned plants and US-, EU-, and ROW-owned plants. D values will also be calculated between UK-owned plants and other UK-owned plants within the same cluster as a comparison between foreign-owned and domestically-owned plants.

As a comparison, and as in section 5.0, the impact of spatial concentration of foreign-owned plants on UK-owned plants will also be estimated for those plants based in the North of England, and the South East. The South East region is presumed to be one of the most productive in the UK, and the North East one of the least productive (Strauss, 2019).

7.3 Methodology

The D values have been calculated between UK-owned plants and foreign-owned plants in each cluster using the Benchmark Cluster configuration defined in the previous section. Using the clusters calculated from the Delgado (2016) clustering algorithm and the D values from the Scholl and Brenner Spatial concentration index, it is possible to estimate whether the spatial concentration between UK-owned plants and Foreign-owned plants has an impact on UK-owned plants within the same cluster.

[52] With the exception of Northern Ireland, due to the distance between the UK mainland and Northern Ireland would skew the D values.

$$y_{it} = \alpha_1 y_{it-1} + \alpha_2 k_{it} + \alpha_3 k_{it-1} + \alpha_4 l_{it} + \alpha_5 l_{it-1} + \alpha_6 n_{it} + \alpha_7 n_{it-1} + \alpha_8 D\,FO_{it} + \alpha_9 D\ UK_{it} + \sum_{y=1986}^{2014} \gamma_y \left[YEAR_t^y\right] + \boldsymbol{X}'\boldsymbol{\beta} + \varepsilon_{it} \tag{7.6}$$

Equation 7-6 Model used to estimate the spatial concertation of foreign-owned plants in relation to UK-owned plants.

Equation (7.6) presents the model used to estimate the impact of the spatial concertation of foreign-owned plants. The D values are logged to make the interpretation of the associated coefficients easier. If the value of the coefficient on the D variable is positive, this indicates that an increase in the spatial concentration of foreign-owned plants has a positive impact on the productivity in the UK-owned plants. If the coefficient is negative, this indicates that an increase in spatial concentration of foreign-owned plants has a negative impact on the productivity in the UK-owned plants. 7.4 Results

This sections**Error! Reference source not found.** presents the results for the impact of the spatial c oncentration of foreign-owned plants within clusters in the North East of England. As in section 5, industrial area dummy variables have been included for Newcastle, Sunderland, and Teesside, to examine the way in which being in these areas impacts upon productivity, and these results can be found in columns (2) and (4). Columns (1) and (2) examine how the increase of spatial concentration of foreign-owned plants impacts on the productivity within UK-owned plants within the same cluster.

The results suggest that an increase in the presence of foreign-owned plants has a positive impact on productivity in UK-owned plants within the same cluster. In this case, although the parament estimate is not statistically significant, it implies that the economic impact of a 10% increase in the concentration of foreign-owned plants lead to a 0.029% increase in productivity in UK-owned plants within the same cluster. However, the estimated effect is not statistically significant. In comparison, an increase in the presence of other UK-owned plants has a negative and significant impact on productivity in UK-owned plants in the same cluster. A 10% increase in the spatial concentration of other UK-owned plants within a cluster resulted in a -0.814% decrease in productivity in UK-owned plants in the same cluster. These findings are similar to studies, such as Grima et al (2015), Hayawaka et al (2013), and Schiffbauer et al (2017), who all found that FDI improved productivity, albeit the findings in this thesis were not significant. It contradicts the findings from papers Benfratello and Sembenelli (2006), and Salis (2008) who found that FDI had a negative impact on productivity.

When including the industrial areas, Newcastle, Sunderland, and Teesside, the sign of the results regarding the spatial concentration of foreign-owned and UK-owned remain the same. The industrial areas also have a similar positive impact on productivity; however, none are significant.

VARIABLES	(1) FO	(2) FO INDUSTRIAL AREA	(3) EU/ROW/US	(4) EU/ROW/US INDUSTRIAL AREA
INTERMEDIATE INPUTS	0.452***	0.458***	0.401***	0.392***
	(6.648)	(6.848)	(3.040)	(3.064)
EMPLOYMENT	0.564***	0.562***	0.630***	0.636***
	(5.823)	(5.781)	(4.959)	(5.089)
CAPITAL	0.201*	0.209**	0.201*	0.209**
	(1.905)	(2.056)	(1.944)	(2.065)
DI FO	0.00289	0.00127	-	-
	(0.327)	(0.140)		
DI UK	-0.0814*	-0.0968*	-0.0894*	-0.107**
	(-1.709)	(-1.898)	(-1.897)	(-2.066)
DI ROW	-	-	-0.000789	-0.000528
			(-0.376)	(-0.251)
DI US	-	-	0.00296	0.00259
			(1.054)	(0.898)
DI EU	-	-	0.000125	-0.000218
			(0.0334)	(-0.0627)
AGE	-0.331**	-0.338**	-0.382**	-0.390***
	(-2.302)	(-2.444)	(-2.523)	(-2.644)
MULTI SIC	-0.0571	-0.0587	-0.0461	-0.0426
	(-0.967)	(-0.981)	(-0.984)	(-0.947)
MULTI REGION	0.142***	0.130**	0.112*	0.108*
	(2.794)	(2.554)	(1.900)	(1.908)
SINGLE	-0.0822	-0.0939	-0.100*	-0.105*
	(-1.426)	(-1.622)	(-1.661)	(-1.731)
HERFINDAHL	0.280**	0.275**	0.259	0.250
	(2.451)	(2.404)	(1.633)	(1.600)
MIDDLESBROUGH	-	0.0112	-	0.0276
		(0.533)		(0.830)
SUNDERLAND	-	0.0404	-	0.118**
		(0.556)		(2.564)
NEWCASTLE	-	0.0538	-	0.0733
		(1.325)		(1.449)
OBSERVATIONS	6,933	6,933	5,980	5,980
AR(1) Z-STATISTIC	-1.783**	-1.723**	-1.571	-1.637
AR(2) Z-STATISTIC	0.456	0.282	-1.190	-1.123
HANSEN TEST	20.02	19.51	9.487	9.075

Cells populated with an "–" indicate variables that have been dropped or not calculated by the regression and cells populated with a an asterisk symbol (*) indicate values that have been suppressed due to the Secure Data Service (SDS) requirements of there being more than 10 enterprises. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7-1 Estimated long-run parameters for foreign ownership effect on ln Gross Output within manufacturing clusters based upon eq. (7.6) for the North East manufacturing 1984-2014. Variables of interest: Di FO, Di EU, Di ROW, and Di US

Columns (3) and (4) separate the foreign ownership into EU, ROW and US ownership types, with column (4) including the industrial area dummies. The increase in the spatial concentration of two ownership types, EU and US, has a positive, but insignificant, impact on the productivity in UK-owned plants within the same cluster, while an increase in the spatial concentration of ROW-owned plants has a negative and insignificant impact on productivity in UK-owned plants within the same cluster. The impact of the presence of other UK- owned firms again has a negative, and significant, impact on the productivity in the UK-owned plants in the same cluster.

When including the industrial area dummy variables, the impact of an increase in the presence of ROW-owned plants within a cluster remains negative and insignificant. The impact on productivity of the increase in the presence of US-owned plants remains positive and insignificant. The sign of the EU concentration coefficient is now negative, although the coefficient is still insignificant.

Examining the industrial area dummy variables, all the regional area coefficients are positive. This suggests that being located in these areas has a positive impact on productivity, with the coefficient for Sunderland being positive and significant. This is consistent with the previous findings in Chapter 5, which also found that being based in Sunderland had a positive and significant impact on productivity within plants.

This suggests that the North East overall benefits from FDI, although the results are not significant, but this is seen most particularly the Sunderland area where the results are both positive and significant. Most specifically benefits appear to stem from investment from the US and the EU. The presence of UK owned plants in clusters with other UK owned firms has a significant and negative impact on productivity

7.4.1 Spatial concentrations and its impact on productivity in different UK regions

Table 7-2 shows the results for the effect of spatial concentration of plants within clusters in the South East and the North of England. Columns (1) and (2) examine the impact of spatial concentration in the North of England and columns (3) and (4) examine the impact of spatial concentration in the South East of England.

VARIABLES	(1) NORTH FO	(2) NORTH EU/ROW/US	(3) SE FO	(4) SE EU/ROW/US
INTERMEDIATE INPUTS	0.729***	0.544***	0.521***	0.514***
	(7.419)	(3.731)	(4.401)	(3.352)
EMPLOYMENT	0.230*	0.346**	0.396***	0.463***
	(1.906)	(2.167)	(3.547)	(3.023)
CAPITAL	0.361*	0.301**	0.128*	0.196*
	(1.867)	(2.333)	(1.772)	(1.794)
DI FO	0.00714	-	-0.139**	
	(1.472)		(-2.339)	
DI UK	-0.0835**	-0.0529**	0.184*	0.0858
	(-2.168)	(-2.249)	(1.852)	(0.820)
DI ROW	-	0.00383**		-0.00935*
		(2.182)		(-1.178)
DI US	-	0.00514**		-0.0240
		(1.999)		(-1.333)
DI EU	-	0.00268		-0.0502
		(0.679)		(-1.473)
AGE	-0.647**	-0.513***	-0.203**	-0.335**
	(-2.188)	(-2.869)	(-2.151)	(-2.076)
MULTI SIC	-0.0972	-0.0453	0.00232	-0.0491
	(-1.362)	(-1.113)	(0.0907)	(-1.340)
MULTI REGION	-0.0600	0.0152	0.0794**	0.0591
	(-1.151)	(0.329)	(2.313)	(1.418)
SINGLE	-0.0814*	-0.0539	0.0106	-0.00244
	(-1.699)	(-1.402)	(0.404)	(-0.0728)
HERFINDAHL	-0.249	0.00253	-0.0625	-0.0652
	(-1.505)	(0.0202)	(-0.612)	(-0.656)
OBSERVATIONS	35,727	31,257	17,061	15,317
AR(1) Z-STATISTIC	-1.200	-2.143**	-4.465***	-3.797***
AR(2) Z-STATISTIC	-1.128	0.0325	-0.767	-0.0986
HANSEN TEST	5.241	1.899	36.65	32.41

Cells populated with an "–" indicate variables that have been dropped or not calculated by the regression and cells populated with a an asterisk symbol (*) indicate values that have been suppressed due to the Secure Data Service (SDS) requirements of there being more than 10 enterprises. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7-2 Estimated long-run parameters for foreign ownership effect on ln Gross Output within manufacturing clusters based upon eq. (7.6) for the North and South East manufacturing 1984-2014. Variables of interest: Di FO, Di EU, Di ROW, and Di US

In the North of England, as with the North East of England, the increase in foreign-owned plants within a cluster has a positive impact on productivity in the UK-owned plants within the same cluster, however the result is insignificant, while the impact of the increase in other UK-owned plants has a negative and significant impact on productivity. When separating the ownership types into the three groups, the increase in the presence of ROW-, EU-, and US-owned plants has a positive impact on productivity on UK-owned plants within the same cluster, with the impact of ROW and US being significant.

In the South East, it is a different picture. The presence of other UK-owned plants has a positive, significant impact on productivity in UK-owned plants in the same cluster, while an increase in the presence of foreign-owned plants has a negative and significant impact on productivity in UK-owned plants in the same cluster. When separating ownership types into EU, ROW and US, the impact of other UK-owned plants is still positive but now insignificant. All the foreign ownership types have a negative impact on productivity in UK-owned plants in the same cluster, with the impact of the spatial concentration of ROW plants being statistically significant.

7.4.2 The effect of spatial concentration of foreign-owned plants interacted with clusters in the North East of England

The following tables present the results when the spatial concentration D values for foreign ownership is interacted with the clusters variable. This was done because, as previously stated, the impact of spatial concentration may differ between industries or, in this case, clusters. Table 7-3 presents the estimated results when interacting the D values of foreign-owned plants and other UK-owned plants within cluster variables to examine the impact on productivity in UK-owned plants in the North East of England.

VARIABLES	FO INTERACTIONS	
INTERMEDIATE INPUTS	0.526***	
	(5.617)	
EMPLOYMENT	0.514***	
	(3.863)	
CAPITAL	0.405***	
	(2.669)	
AGE	-0.578***	
	(-2.854)	
MULTI SIC	-0.173**	
	(-2.237)	
MULTI REGION	0.0779	
	(1.057)	
SINGLE	-0.199**	
	(-2.189)	
HERFINDAHL	0.619	
	(1.299)	
CLUSTER INTERACTION	**Di FO**	**Di UK**
1 FERROUS METALS AND MANUFACTURING	-0.344	-1.173
	(-0.957)	(-1.130)
2 NON-FERROUS METAL MANUFACTURING	-0.0191	0.0238
	(-0.576)	(0.146)
3 METAL MANUFACTURING	0.0562	-0.262*
	(1.291)	(-1.716)
4 MINERAL EXTRACTION	*	-0.256
	-	(-1.467)
5 OTHER MINERALS EXTRACTION	*	-0.126
		(-0.569)
6 MINERAL MANUFACTURING	-0.0289	-0.275***
	(-0.451)	(-2.633)
7 BUILDING MATERIALS	-0.0418	-0.285***
	(-1.138)	(-3.099)
8 MISCELLANEOUS MANUFACTURING	0.172	-0.234
	(1.230)	(-1.136)
9 BREAD AND BISCUITS	-0.0275	-0.207***
	(-1.240)	(-2.651)
10 LARGE TRANSPORT MANUFACTURING	*	0.643***

	-	(3.979)
11 SOAPS AND PERFUMES	-0.127	-0.00822
	(-1.175)	(-0.0138)
12 GRAIN AND STARCH	*	-4.372
		(-0.958)
13 PET FEEDS	*	-0.662
		(-1.450)
14 LEATHER WORKING	*	1.039
		(0.0971)
15 PAINTS	0.00746	-0.201
	(0.261)	(-1.473)
16 PROCESSING OF FOOD STUFFS	*	-0.0138
		(-0.0986)
17 EXPLOSIVES AND ORDANCE	*	-0.332***
		(-2.796)
18 COOKING FATS AND OILS	-	-
19 PROCESSING MEATS	0.0553**	-0.0652
	(1.997)	(-0.571)
20 SUGAR	-	-
21 CONFECTIONARY	-0.0128	-0.317
	(-0.378)	(-1.476)
22 PAPER PRODUCTS	-0.0206	-0.113
	(-0.375)	(-1.253)
23 PRINTING PRODUCTS	0.133**	-0.475**
	(2.481)	(-2.192)
24 DISTILLING AND COMPOUNDING	-	-
25 BREWING AND TOBACCO	-0.0195	0.0633
	(-1.139)	(0.475)
26 RECREATIONAL MANUFACTURING	-0.0997**	-0.0294
	(-2.121)	(-0.194)
27 PRECISION APPARATUS	-0.109**	-0.190
	(-2.358)	(-1.229)
28 INORGANIC AND ORGANIC CHEMICALS	-0.0920*	-0.294**
	(-1.910)	(-2.477)
29 ESSENTIAL OILS	*	-1.349
		(-1.136)
30 CHEMICAL AND ADHESIVES	0.503*	-0.625***
	(1.738)	(-2.872)

31 MAN MADE FIBRES	*	-2.132
		(-1.021)
32 RUBBER TYRES	*	-0.167
		(-1.614)
33 PLASTIC AND RUBBER PRODUCTS	0.213**	-0.273*
	(1.990)	(-1.817)
34 ELECTRONIC EQUIPMENT	-0.00758	-0.217
	(-0.0780)	(-1.376)
35 WOOD MANUFACTURING	0.0150	-0.0122
	(0.343)	(-0.0974)
36 WALL COVERINGS	*	-0.480*
		(-1.885)
37 SYNTHETIC RUBBER	-	-
38 TRACTORS	-	-
39 VEHICLES	0.0396	- 0.350***
	(0.636)	(-2.828)
40 TEXTILES	-0.129*	-0.912**
	(-1.762)	(-2.260)
41 OTHER TEXTILES	*	-0.126
		(-0.637)
42 CLOTHING	0.0122	0.253*
	(0.702)	(1.838)
43 METAL AND CHEMICAL MACHINERY	0.365*	-0.752**
	(1.804)	(-2.028)
44 COMMERCIAL MACHINERY	0.0791**	-0.450**
	(2.068)	(-2.421)
45 MINING MACHINERY	-0.144***	-0.237
	(-2.891)	(-1.299)
46 OTHER MANUFACTURING	-0.00715	0.509**
	(-0.118)	(2.022)
OBSERVATIONS	6,933	
AR(1) Z-STATISTIC	-2.286**	
AR(2) Z-STATISTIC	0.679	
HANSEN TEST	29.65	

Cells populated with an "–" indicate variables that have been dropped or not calculated by the regression and cells populated with a an asterisk symbol (*) indicate values that have been suppressed due to the Secure Data Service (SDS) requirements of there being more than 10 enterprises. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7-3 Estimated long-run parameters for foreign ownership effect on ln Gross Output within manufacturing clusters by interacting foreign ownership with individual clusters based upon eq. (7.6) for the North East manufacturing 1984-2014.

The results in the previous section suggest that the presence of UK-owned plants within a cluster has a negative impact on the productivity of UK-owned plants in the same cluster. In 35 out of the 46 clusters, an increase in the presence of other UK-owned plants has a negative impact on the productivity of other UK-owned plants within the same cluster. Out of those 35 clusters, the negative impact of the presence of other UK-owned plants has a significant impact on productivity in UK-owned plants in 14 of the clusters. There are six clusters where an increase in the presence of other UK-owned plants has a positive impact on productivity in UK-owned plants in the same cluster, with three of those clusters experiencing a positive and significant impact on productivity in UK-owned plants.

The increase in foreign-owned plants within a cluster has a positive impact on productivity in UK owned plants within the same cluster in 12 of the 46 clusters, with the impact having a positive and significant impact in six of those clusters. There are clusters where the increase in the presence of foreign-owned plants has a negative impact on productivity within UK owned plants, with 16 of the clusters having a negative impact on productivity. Out of these 16 clusters, five have a negative and significant impact on productivity in UK-owned plants.

VARIABLES	EU/ROW/US INT			
INTERMEDIATE INPUTS	0.514***			
	(4.833)			
EMPLOYMENT	0.551***			
	(3.708)			
CAPITAL	0.220**			
	(2.152)			
AGE	-0.424**			
	(-2.663)			
MULTI SIC	-0.0731*			
	(-1.528)			
MULTI REGION	0.044			
	(0.755)			
SINGLE	-0.125**			
	(-2.217)			
HERFINDAHL	-0.0203			
	(-0.081)			
CLUSTER INTERACTION	**Di UK**	**Di ROW**	**Di EU**	**Di US**
1 FERROUS METALS AND MANUFACTURING	0.22	*	0.065	0.0271
	(0.373)		(0.93)	(0.369)
2 NON-FERROUS METAL MANUFACTURING	-0.0605	-0.00144	-0.00797	-0.00487
	(-0.462)	(-0.0986)	-0.234)	(-0.24)
3 METAL MANUFACTURING	-0.158	-0.00126	0.0309*	0.0172
	(-1.208)	(-0.0563)	(1.655)	(0.97)
4 MINERAL EXTRACTION	-	*	-	-
5 OTHER MINERALS EXTRACTION	-14.44	-	*	-
	(-0.849)			
6 MINERAL MANUFACTURING	-0.189**	*	-0.00221	-0.0331
	(-2.183)		(-0.212)	(-0.741)
7 BUILDING MATERIALS	-0.0874	*	-0.0327	*
	(-0.77)		(-1.05)	
8 MISCELLANEOUS MANUFACTURING	-0.372*	0.00426	-0.0171	0.071
	(-1.857)	(0.432)	(-0.215)	(1.092)
9 BREAD AND BISCUITS	-0.115	*	0.0406**	*
	(-1.25)		(2.426)	
10 LARGE TRANSPORT MANUFACTURING	0.439*	*	*	-0.0291
	(1.695)			(-0.595)
11 SOAPS AND PERFUMES	-0.563**	*	*	-0.104***
	(-2.087)			(-2.712)

CLUSTER INTERACTION	DI UK	DI ROW	DI EU	DI US
12 GRAIN AND STARCH	-	-	-	-
13 PET FEEDS	-	-	*	-
14 LEATHER WORKING	-	-	-	-
15 PAINTS	-0.0877	0.0105	-0.00113	*
	(-0.705)	(0.604)	(-0.0504)	
16 PROCESSING OF FOOD STUFFS	-0.149	*	*	*
	(-0.844)			
17 EXPLOSIVES AND ORDANCE	1.039*	*	-	*
	(1.934)			
18 COOKING FATS AND OILS	-	-	-	-
19 PROCESSING MEATS	-0.338**	*	0.0119	*
	(-2.036)		(0.406)	
20 SUGAR	-	-	-	-
21 CONFECTIONARY	-0.234*	*	0.00616	*
	(-1.653)		(0.125)	
22 PAPER PRODUCTS	-0.094	*	-0.0115	0.000361
	(-1.389)		(-0.648)	(0.0167)
23 PRINTING PRODUCTS	-0.085	*	-0.017	0.022
	(-0.816)		(-1.353)	(1.256)
24 DISTILLING AND COMPOUNDING	-	-	-	-
25 BREWING AND TOBACCO	-0.101	*	*	*
	(-0.688)			
26 RECREATIONAL MANUFACTURING	0.0159	*	*	0.00625
	(0.0986)			(0.23)
27 PRECISION APPARATUS	-0.185	*	-0.0293	-0.00263
	(-1.213)		(-1.334)	(-0.105)
28 INORGANIC AND ORGANIC CHEMICALS	-0.193**	*	0.0191	-0.0531*
	(-2.198)		(0.624)	(-1.837)
29 ESSENTIAL OILS	-	-	-	-
30 CHEMICAL AND ADHESIVES	-0.384***	*	0.0302	0.0269
	(-3.137)		(0.527)	(0.391)
31 MAN MADE FIBRES	-	-	-	-
32 RUBBER TYRES	0.225	*	*	*
	(0.0862)			

CLUSTER INTERACTION	DI UK	DI ROW	DI EU	DI US
33 PLASTIC AND RUBBER PRODUCTS	-0.223**	0.0301	0.0112	0.183***
	(-2.019)	(1.081)	(0.217)	(2.796)
34 ELECTRONIC EQUIPMENT	-0.283**	-0.0201	0.00849	0.119
	(-2.08)	(-1.625)	(0.422)	(1.574)
35 WOOD MANUFACTURING	0.0375	*	0.0533	0.0117
	(0.388)		(1.569)	(0.9)
36 WALL COVERINGS	-	-	-	-
37 SYNTHETIC RUBBER	-	-	-	-
38 TRACTORS	-	-	-	-
39 VEHICLES	-0.149*	0.0279**	0.00199	-0.00038
	(-1.94)	(2.27)	(0.0726)	(-0.0121)
40 TEXTILES	-0.681**	*	*	*
	(-2.286)			
41 OTHER TEXTILES	0.181	*	*	*
	(1.077)			
42 CLOTHING	0.11	0.00641	0.00781	-0.00928
	(0.893)	(0.936)	(1.114)	(-0.609)
43 METAL AND CHEMICAL MACHINERY	-0.254	-0.0165	0.0595	0.0294
	(-1.594)	(-1.303)	(1.626)	(0.427)
44 COMMERCIAL MACHINERY	-0.241	-	0.0358	0.0642*
	(-1.552)		(1.511)	(1.779)
45 MINING MACHINERY	-	-	-	-
46 OTHER MANUFACTURING	0.194	0.0860**	-0.0964*	0.144*
	(0.934)	(2.166)	(-1.836)	(1.881)
OBSERVATIONS	5,980			
AR(1) Z-STATISTIC	-1.303			
AR(2) Z-STATISTIC	-1.542			
HANSEN TEST	9.61			

Cells populated with an "–" indicate variables that have been dropped or not calculated by the regression and cells populated with a an asterisk symbol (*) indicate values that have been suppressed due to the Secure Data Service (SDS) requirements of there being more than 10 enterprises. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7-4 Estimated long-run parameters for foreign ownership effect on ln Gross Output within manufacturing clusters by interacting foreign ownership groups with individual clusters based upon eq. (7.6) for the North East manufacturing 1984-2014.

The table above separates the ownership type into EU, ROW and US and interacts the dummy variables with the cluster variables as well as other UK-owned plants. The aim is to examines the way in which the increase in the presence of EU-, US-, and ROW-owned plants as well as other UK-owned plants impact upon productivity in the UK-owned plants in the same cluster. As with the previous results, the presence of UK-owned plants has a negative impact in 24 out of the 46 clusters. The increase in the presence of other UK-owned plants had a significant negative impact in 11 of those clusters. In nine of the clusters, an increase in the concentration of UK-owned plants had a positive impact on the productivity in UK-owned plants, with the impact being significant in two of the clusters. EU-owned plants had a positive impact on productivity in UK-owned plants in 14[53] of the 46 clusters, with the impact being significant in two of those clusters: 3 Metal Manufacturing and 9 Bread and Biscuits.

There are six clusters[54] which are in the top ten for the number of plants and level of employment, and these are clusters where the North East traditionally has a comparative advantage such as in metal manufacturing and chemical production. However, the impact is only significant in Cluster 3 Metal Manufacturing.

In the North East, most of the clusters experienced a positive impact on productivity when there was an increase in the presence of EU-owned plants within those clusters. There are four clusters in the North East where there is an above national average regional concentration of plants and in these clusters EU-owned plants have a positive productivity impact. These are Cluster 1, Ferrous Metals and Manufacturing, Cluster 28, Inorganic and Organic Chemicals, Cluster 9, Bread and Biscuits and Cluster 30, Chemical and Adhesives . The impact is positive and significant only in Cluster 9, Bread and Biscuits.

The increase in the spatial concentration of EU-owned plants has a negative impact on productivity in UK-owned plants in nine[55] of the 46 clusters, with the impact being significant in one of the nine clusters, Cluster 46, Other Manufacturing. In terms of regional concentration of cluster, these clusters

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[53] The clusters where an increase in the presence of EU owned plants has a positive impact on productivity are: 1 Ferrous metals and manufacturing, 3 Metal Manufacturing, 9 Bread and Biscuits, 19 Processing meats, 21 Confectionary, 28 Inorganic and organic chemicals, 30 Chemical and Adhesives, 33 Plastic and rubber products, 34 Electronic Equipment, 35 Wood manufacturing, 39 Vehicles, 42 Clothing, 43 Metal and Chemical Machinery, and 44 Commercial Machinery.

[54] These clusters are: 3 Metal Manufacturing, 28 Inorganic and organic chemicals, 33 Plastic and rubber products, 34 Electronic Equipment, 39 Vehicles, and 43 Metal and Chemical Machinery

[55] The clusters where an increase in the presence of EU owned plants has a negative impact on productivity are: 2 Non-ferrous metal Manufacturing, 6 Mineral Manufacturing, 7 Building Materials, 8 Miscellaneous Manufacturing, 15 Paints, 22 Paper Products, 23 Printing products, 27 Precision Apparatus, and 46 Other manufacturing

have a low level of regional concentration in the North East, which suggests their limited importance to the North East economy.

The increase in the concentration of US-owned plants also has a positive impact on productivity in 14[56] of the 46 clusters. The clusters where the impact of an increase in US-owned plants is positive and significant are: Cluster 33, Plastic and Rubber Products, Cluster 44, Commercial Machinery, and Cluster 46, Other Manufacturing. The results show that if there was a 10% increase in US plants within these clusters, it would result in a 1.8% increase in productivity in UK-owned plants in Cluster 33, Plastic and Rubber Products, a 0.6% increase in productivity in UK-owned plants in Cluster 44, Commercial Machinery and a 1.4% increase in productivity in UK-owned plants in Cluster 46, Other Manufacturing.

In seven clusters,[57] the increase in the presence of US-owned plants has a negative impact on productivity in UK-owned plants in the same cluster, with the impact being significant in two of the clusters: Cluster 11, Soaps and Perfumes and Cluster 28, Inorganic and Organic Chemicals. For the North East, Cluster 28, Inorganic and Organic Chemicals has an above average regional concentration for both the number of plants and level of employment and is an important cluster for the regional economy. However, the presence of US-owned plants can be seen to be having a detrimental impact on UK-owned plants. This could be due to crowding out of UK-owned plants or by US-owned plants preventing their knowledge from being assimilated by UK-owned plants in the same cluster.

The increase in the presence of ROW-owned plants has a positive impact in six of the clusters, with two of these clusters experiencing a significant impact on productivity. One of these clusters where the impact is positive and significant is Cluster is 39, Vehicles. The results indicate that a 10% increase in ROW plants increased productivity by 0.3% in UK-owned plants in the same cluster. The North East is home to Nissan, based in Sunderland, which is perceived to be one of the most productive car plants in Europe. It appears from this work that being in this cluster with the Nissan factory is beneficial to UK-owned plants. This is likely to be due to Nissan sharing knowledge, manufacturing techniques, and management and process expertise with their supply chain, ensuring they receive appropriate inputs

[56] These clusters are: 1 Ferrous metals and manufacturing, 3 Metal Manufacturing, 8 Miscellaneous Manufacturing, 22 Paper Products, 23 Printing products, 26 Recreational Manufacturing, 30 Chemical and Adhesives, 33 Plastic and rubber products, 34 Electronic Equipment, 35 Wood manufacturing, 43 Metal and Chemical Machinery, 44 Commercial Machinery, 46 Other manufacturing.

[57] These clusters are: 2 Non-ferrous metal Manufacturing, 6 Mineral Manufacturing, 10 Large transport Manufacturing, 11 Soaps and Perfumes, 27 Precision Apparatus, 28 Inorganic and organic chemicals, 39 Vehicles, and 42 Clothing.

for their vehicles. This example of FDI should be acknowledged by policy makers and considered as a template when trying to incentivise further FDI projects within regions. There are four clusters where the increase of ROW-owned plants has a negative impact on productivity in UK-owned plants in the same cluster, however these results are insignificant.

7.4.3 The effect of spatial concentration of foreign-owned plants over time in the North East of England

In this section I examine the impact of the spatial concentration of plants over time in the North of East of England. This is estimated over time for foreign-owned plants in the North East of England by interacting the Di values for the different ownership types with the Year variable, to estimate values for each year. These points are then plotted to obtain the trend line over time, showing the way in which the spatial concentration of foreign-owned plants influences the productivity in UK-owned plants in the same cluster.

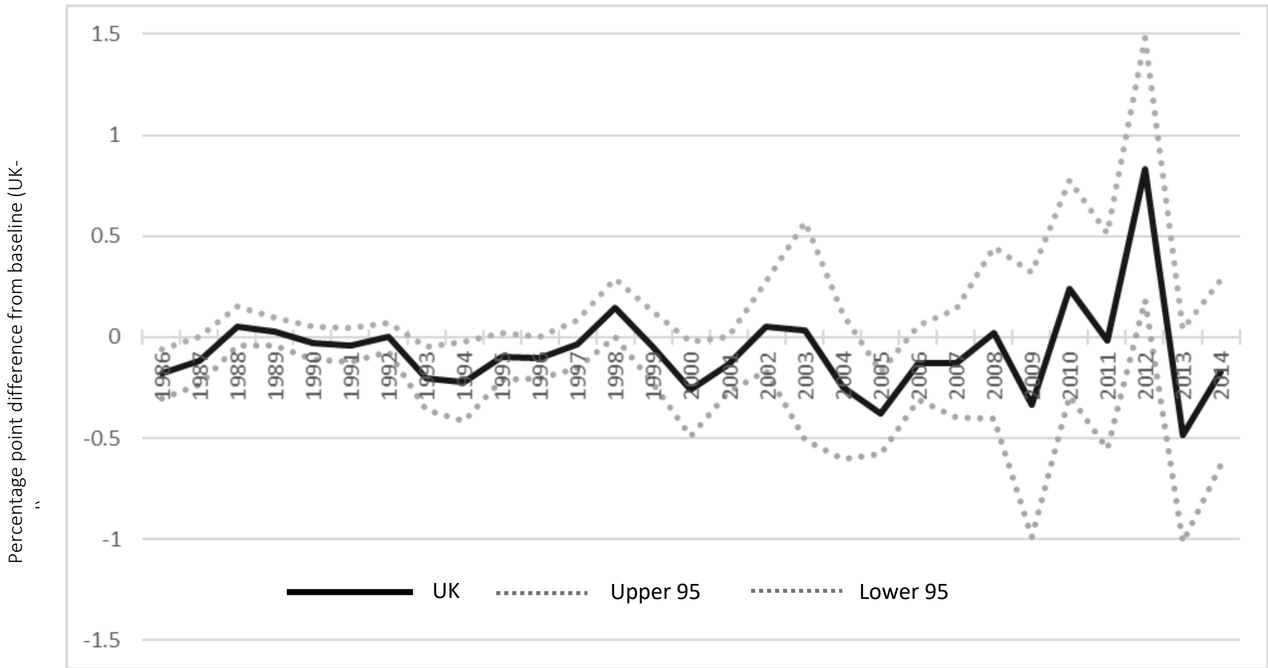

Figure 7-2 The spatial concentration effect over time between UK- and other UK-owned plants in the North East of England

Figure 7-2 presents the impact of the spatial concentration of UK-owned plants on productivity in other UK-owned plants within the same cluster. There are periods where the effect of other UK-owned plants is significant, those being between 1986 to 1987, 1993 to 1994, 2000 to 2001 and 2005 where the impact is significant and negative. There are two of periods where the effect is positive, and they are: 1998 and 2012.

This negative relationship between UK-owned plants and productivity could stem from a race to the bottom relationship, with firms competing to supply the larger foreign-owned plants within the supply chains. Incumbent firms are pressured into lowering prices to compete with the newer UK plants entering the cluster. It could also be explained by these UK-owned plants preventing spillovers occurring between them, as Javorcik (2004) found, or having no incentive to innovate new more effective practices, as they have learnt to successfully compete for contracts by meeting minimum specifications and volume requirements as cheaply as possible, meaning they avoid incurring any additional costs associated with R&D. This would not be a desirable or sustainable long-term position for UK-owned plants, as they may not then be able to meet new or additional requirements that may be imposed by the larger foreign-owned plant, or to compete for business beyond that customer. Due to the interdependencies between the UK-owned plants and these larger, foreign-owned plants, should these large plants decide to pull out, as a result of any additional unexpected costs, it would devastate the supply chains.

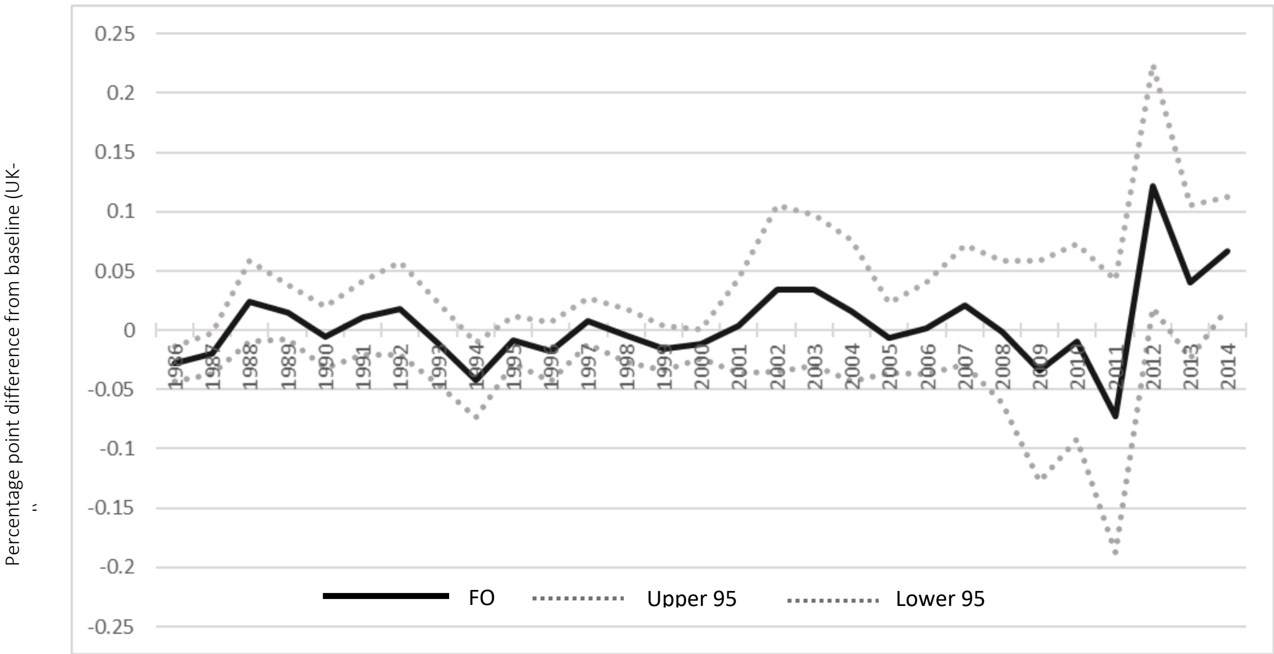

Figure 7-3 The effect of the spatial concentration Foreign-owned plants on UK-owned plants in the North East of England

Figure 7-3 shows the impact of the spatial concentration of foreign-owned plants on UK-owned plants within the same cluster.

As with the impact of other UK-owned plants, the line remains close to zero, although more of the line is above zero when compared with the other UK-ownership effect. The effect of foreign ownership is positive and significant in 2012 and 2014, with a negative impact of foreign-owned plants being shown in 1986, 1994, and 2000.

The following figures show the effect of the spatial concentration of EU-, ROW-, and US-owned plants in clusters in the North East of England over time. The presence of other UK-owned plants was also estimated and had similar results to the previous estimation above; the figure can be found in Appendix 14.3.

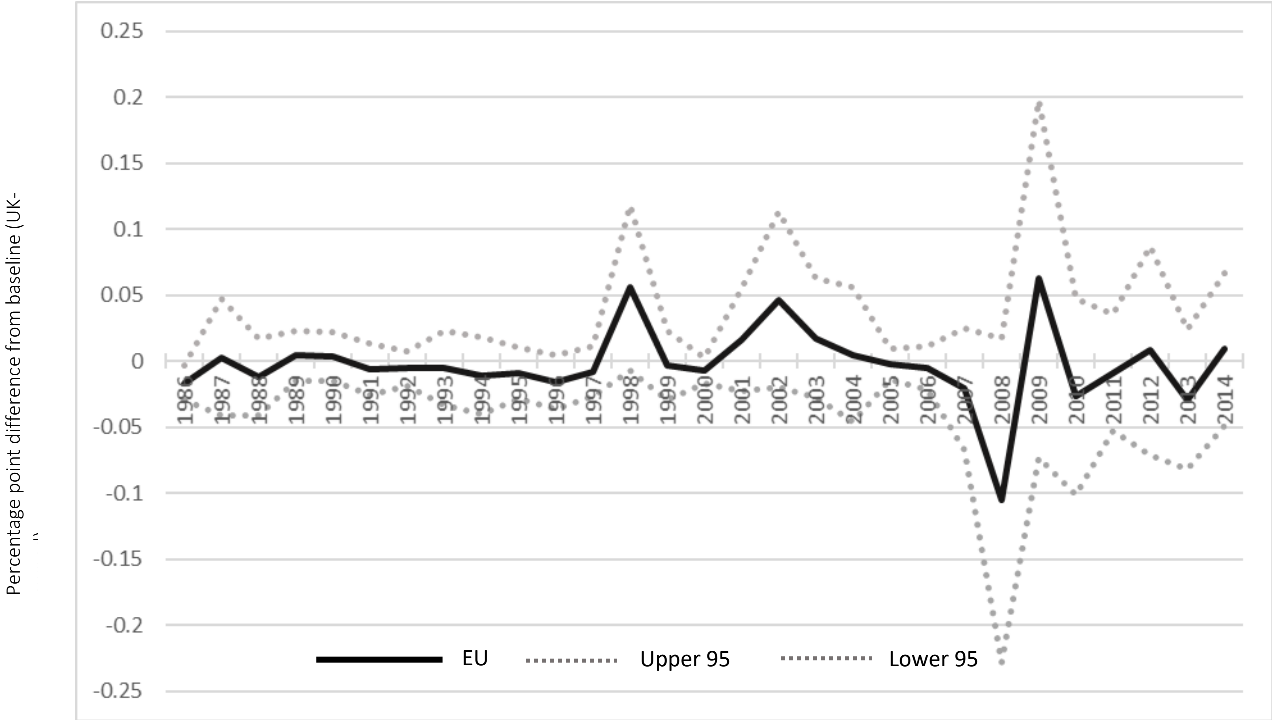

Figure 7-4 The Effect of the spatial concentration of EU-owned plants to UK-owned plants in the North East of England

Figure 7-4 shows the impact EU-owned plants have on productivity in UK-owned plants in the same cluster over time. As with the other UK-owned plants, there is no period where EU-owned plants have a statistically significant impact on productivity in UK-owned plants.

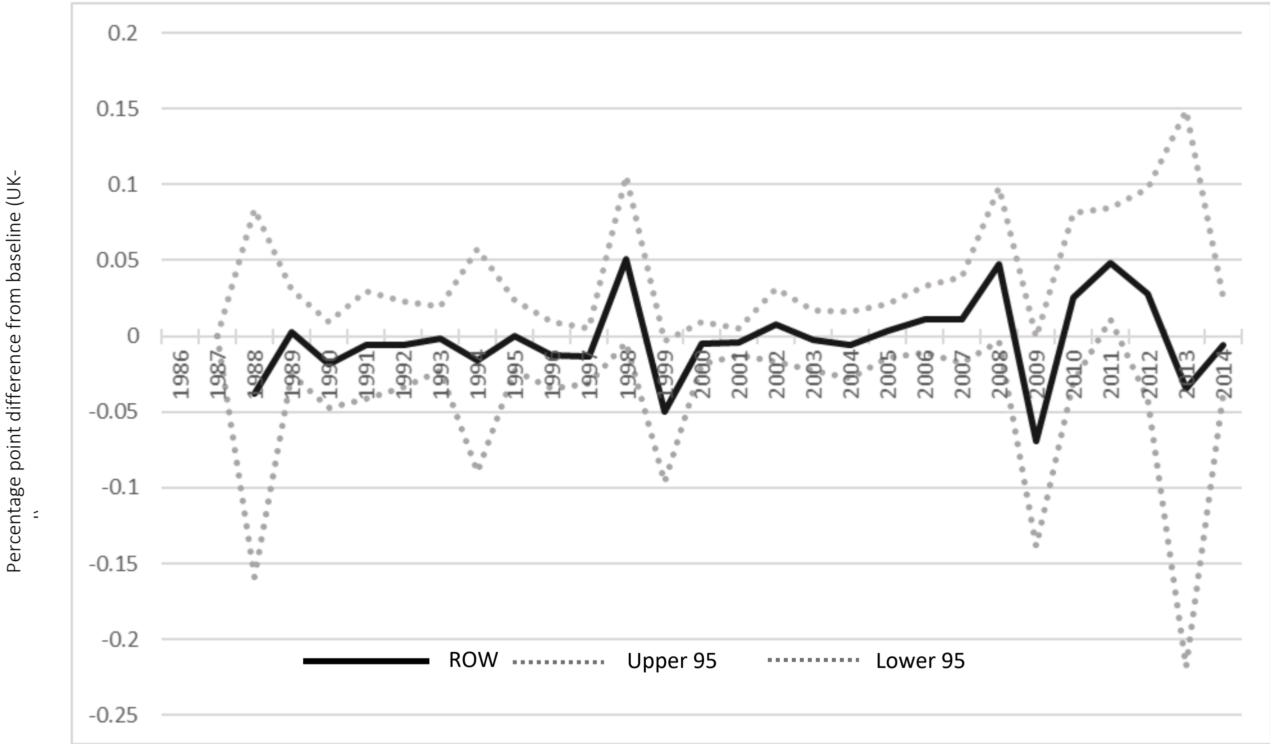

Figure 7-5 The Effect of the spatial concentration of ROW-owned plants to UK-owned plants in the North East of England

Figure 7-5 shows the impact of ROW-owned plants on productivity in UK-owned plants in the same cluster. Unlike the other UK-owned and EU-owned plants, there are two periods where ROW-owned plants have a significant impact on productivity in UK-owned plants. In 1999, ROW-owned plants had a negative impact on productivity in UK-owned plants in the same cluster, and in 2011, when ROW-owned plants had a positive impact on productivity in UK-owned plants in the same cluster.

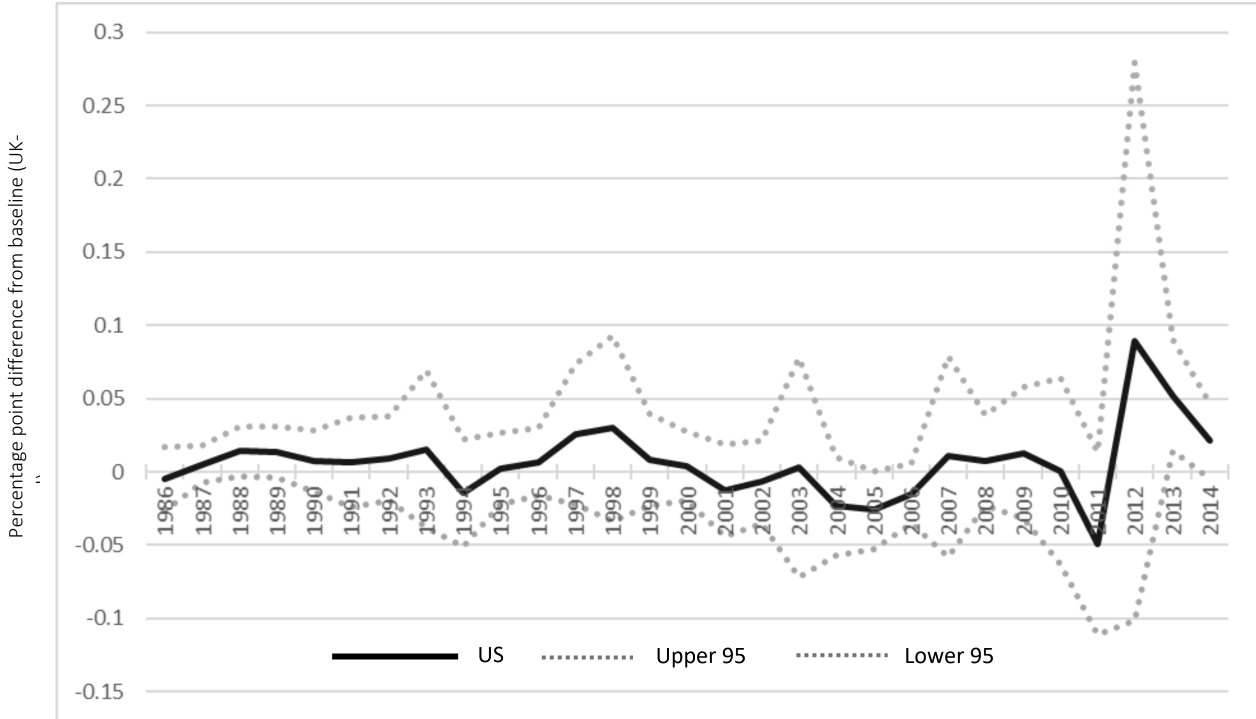

Figure 7-6 The Effect of the spatial concentration of US-owned plants to UK-owned plants in the North East of England

Figure 7-6 shows the impact of US-owned plants on productivity in UK-owned plants. For the majority of the time period, the impact of the presence of US-owned plants was not significant. In 2013, US-owned plants had a positive and significant impact on the productivity of UK-owned plants within the same cluster.

When examining the impact of the presence of foreign-owned plants, as well as the different ownership groups, over time, the impact is generally insignificant and small. Comparing this to the impact of the presence of UK-owned plants within clusters over time, the effect of the presence of foreign-owned plants is a tenth of the size.

7.5 Conclusion

This chapter sets out to establish the impact of the spatial concentration of foreign-owned plants on productivity within UK-owned plants in the same clusters. Using the cluster configuration developed in the previous chapter, the spatial concentration of foreign-owned plants in relation to UK-owned plants within the same clusters has been calculated using the Scholl and Brenner (2016) Spatial concentration index. These D values can then be used to estimate how the concentration of foreign ownership impacts upon productivity in UK-owned plants. The Scholl and Brenner index does not use arbitrary boundaries but inverted distances, which overcomes the MAUP which is present in other techniques.

Overall, the impact of an increase in the spatial concentration of foreign-owned plants on the productivity in UK-owned plants is positive but insignificant. When separating the ownership types, EU- and US-owned plants have a positive but insignificant impact on UK-owned plant productivity within the same cluster, while the impact of the presence of ROW-owned plants is negative. When including the industrial area dummy variables, the estimated effect of the presence of EU-owned plants is now negative, but still insignificant. When examining the impact of the increase of spatial concentration of foreign ownership within specific clusters, there was a positive and significant impact within six clusters, and a negative and significant impact within five of the clusters.

An increase in the spatial concentration of EU-owned plants within a cluster has a positive and significant impact in two clusters, and a negative and significant impact in one cluster. The increase in the spatial concentration of US plants within a cluster has a positive and significant impact in four clusters, and a negative and significant impact in one cluster, while the impact of the presence of ROW-owned plants in a cluster has a positive and significant impact in one cluster.

Most of the EU-owned plants and EU employment are based within Cluster 8, Miscellaneous Manufacturing and Cluster 46, Other Manufacturing. In both clusters, the presence of EU-owned plants has a negative impact upon UK-owned plants in the same clusters. According to the Location Quotients calculated for the previous chapter, Cluster 8, Miscellaneous Manufacturing has a slightly above the national average presence in the North East of England, while Cluster 46, Other Manufacturing has a below national average presence. This could suggest that neither of these clusters is important for the North East economy.

Where ROW-owned plants are based in clusters with an above the national average level of concentration, such as Cluster 39, Vehicles, and Cluster 34, Electronic Equipment, it implies that these clusters are more important to the North East economy. The presence of ROW-owned plants has a positive and significant impact on UK-owned plants within Cluster 39, Vehicles. In light of the EU referendum in 2016 and the negotiation of the Trade Cooperation and Agreement deal with the EU, Nissan raised concern at the possible lack of access to the EU market in 2018. The UK and the North East should be concerned at the potential loss of such a high-level employer with high production levels and a high value product. Furthermore, it is shown that ROW-owned plants within the Vehicle Cluster have a positive and significant impact on productivity in UK-owned plants in the same cluster, indicating that a 10% increase in ROW-owned plants increased productivity by 0.3% in UK-owned plants in the same cluster.

There is a clear overlap between the employment and positive spillover metrics in Cluster 39, Vehicles, likely to reflect the presence of Nissan in the region. The number of plants is low, in the case of Nissan a single plant, but the plant is very large and employs significant numbers, while having a positive impact on the UK-owned supply chain firms. It can therefore be deduced that the region is highly reliant on this manufacturer for employment and prosperity, and should Nissan choose to leave the region, or become destabilised as a company, the negative consequences for the region would be severe. In policy terms this suggests that policies to retain and support Nissan in the region are vital, but further diversification from this heavy reliance would increase the region's resilience in the event of future downturns within this industry and this specific company.

A similar pattern is seen from US-owned plants based within North East clusters with an above national average concentration, such as Cluster 33, Rubber and Plastic Products, Cluster 34, Electrical Equipment, and Cluster 39, Vehicles. This is most evident in Cluster 33, Rubber and Plastic Products where an increase in the presence of US-owned plants has a positive and significant impact on productivity in UK-owned plants in the same cluster. These results indicate that a 10% increase in the presence of US-owned plants, increased productivity by 1.8% in UK-owned plants. As a comparison, D values are also estimated for UK-owned plants, to examine the impact of the increase in the spatial concentration of other UK-owned plants within the same cluster. In every estimation, the impact of an increase in the presence of UK-owned plants within a cluster has a significant and negative impact on the productivity in other UK-owned plants within the same cluster.

The South East region, is the only region in this study where this does not hold. The impact of the presence of foreign-owned plants here is negative and significant but the impact of the presence of UK-owned plants is positive and significant. This could be explained by foreign-owned plants establishing in the South East in order to benefit from spillovers from other UK-owned plants, exploiting their knowledge, and expertise. This is presumed to be as a result of the South East being one of the most productive regions in the UK.

The findings in this chapter are similar to those of Harris and Robinson (2002) where the impact of FDI spillovers is not consistent across all clusters; it was found that the influence could be both positive and negative. This could be due to heterogeneity within each cluster, for example reflecting differing technological capabilities of the plants included. Javorcik (2004) and Ha, Holmes, and Hassan (2023) found that spillovers occurred within vertical linkages, rather than horizontal, due to competition. The large foreign-owned firms cascaded advantages to their supply chain, but these businesses are then reluctant to share this learning more widely to preserve those advantages for themselves when competing for further contracts from these large businesses. This potentially accounts for the negative impact on UK-owned firms.

The importance of locating in the North East region for foreign investors may be because the region is, or has been, geographically well situated, and well linked through ports and shipping services with North West Europe. The region can act as a conduit for goods into the EU from an area with relatively low wages and land costs, from plants benefitting from all types of investment. It is important in policy terms that investment therefore is fostered which does not solely rely on these “race to the bottom” factors, leaving the North East as an arm’s length supplier of low value components, with little value added to its indigenous industries. Rather investment should be promoted such as that by Nissan, in which finished goods are exported to the EU, with investment in research, training and development of UK-owned supply chain firms.

In future work, it would be useful to compare the effect on productivity of the presence of foreign-owned plants between clusters, as well as within clusters, as Girma and Wakelin (2002) and Haskel et al (2007) did in examining how FDI impacted upon domestic plants when they were based within the same industry.

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8. Conclusion

This thesis set out to do the following:

1. To establish if there is a productivity advantage in foreign-owned firms over UK-owned firms in the North East of England.
2. To establish a reliable mechanism for assessing the impact of foreign-owned investments in the North East, which is comparable across multiple UK regions.
3. To analyse the impact of the presence of foreign-owned firms on productivity in UK-owned firms in the same cluster by region.

I have set the North East in its historical context, as a manufacturing region. It used to be home to a large, prosperous, and innovative heavy manufacturing sector which was able to develop from local resources of coal and iron ore as well as excellent transport innovations and linkages, including developing railways and access to large seaports. During this rapid development in the nineteenth century, the North East regional characteristics included high levels of research and innovation, and a concentration of interdependent, highly developed, productive industries. Following the Second World War, these heavy industries declined, due to lack of investment in an industrial rebuilding strategy, reduced markets and competition from cheaper alternative products and suppliers, resulting in high unemployment, and regional decline. Governments of all political views attempted to address this decline from the 1980s by attracting FDI to the region under the assumption that this would support the region's regeneration. Positive spillovers were assumed to take place, before the complexities of the impact of host regional characteristics had been understood.

This thesis found that the impact of foreign ownership on productivity in the North East was positive when compared with UK-owned plants, although the impact was statistically insignificant when addressing foreign investment as a whole. These findings are similar to studies, such as Girma et al (2015), Hayawaka et al (2013), and Schiffbauer et al (2017), who all found that FDI improved productivity. It contradicts the findings from papers Benfratello and Sembenelli (2006), and Salis (2008) who found that FDI had a negative impact on productivity.

When the foreign ownership classification was broken down into EU-, US-, and ROW-owned plants, then differences in the significance of the impact on productivity emerge. It was found that both the US and ROW ownership groups have a positive and a significant impact on productivity when compared with the UK-owned plants. EU ownership had a positive impact, but it was not significant. These results are similar to other studies' findings which have examined the impact of foreign ownership in the UK. Harris and Moffat (2015, 2017), and Conyon, Girma, Thompson, and Wright (2002) both found that US-owned plants performed better than other ownership groups.

Analysis of the impact of FDI on recipient plants however does not give an indication of the impact of foreign-owned plants upon productivity in UK-owned plants within the supply chains. To examine this, clusters were used as they capture more inter-industry linkages, rather than industry classifications alone as some of these fail to capture such linkages altogether. These clusters were created by adapting the Delgado et al (2016) clustering algorithm, which combines regional and national matrices to capture the inter-industry linkages. This method also assesses the linkages within the cluster configuration to ensure the clusters are the most accurate possible. The UK cluster configuration was created using location matrices for establishments and employment, along with input-output and occupational type matrices, to create a cluster configuration containing 46 clusters.

My cluster analysis method is unique in being able to analyse regional economies across the UK in this way. It can provide an evidence base for each region to identify their individual investment needs and to produce their own bespoke investment strategies, which minimise negative impacts on their existing UK-owned industry and maximise benefits from FDI and positive spillovers.

Using the cluster configuration defined by the Delgado et al (2016) algorithm and the Distance Index developed by Scholl and Brenner (2016), it was possible to calculate the spatial concentration of foreign-owned plants in relation to UK-owned plants within these clusters. No other study has investigated UK manufacturing sector spillovers in this manner.

A comparison was undertaken by analysing the South East and the North of England as a whole, alongside the North East, and identifying any patterns in productivity and positive spillovers. These comparator regions were selected because the South East of England is one of the most productive regions in the UK, and has very different host regional characteristics to the North East, with high wage costs, high land prices, and excellent transport links within the region and to central London and Europe. The North of England region more generally has been used by Governments to measure the effectiveness of FDI in the region, without considering the specific issues associated with the North East of England.

The most important clusters for the North East regional economy, ranked by employment and number of plants, were not too dissimilar from those identified as significant in the North of England generally, as well as the South East, particularly regarding Cluster 3, Metal Manufacturing, and Cluster 34, Electronic Equipment which appear from this study to have national significance. National support for these industries is likely to benefit all of these regions, but perhaps most significantly in the North East investment in Cluster 3, Metal Manufacturing would be beneficial as employment levels suggest it may be less productive here, than in the South East.

This thesis found that, in the North East, the impact of an increase in the presence of foreign-owned plants on productivity in UK-owned plants in the same cluster, was positive but statistically insignificant. This is similar to the findings of Haskel et al (2007) and Girma and Wakelin (2002).

Separating foreign ownership into the different ownership groups revealed that an increase in the presence of both EU- and US-owned plants had a positive but statistically insignificant impact on productivity in UK-owned plants within the same cluster. The impact of ROW-owned plants was found to be negative, but again, statistically insignificant. When including the industrial area dummy variables for Sunderland, Middlesbrough and Newcastle in the model, the impact of the presence of EU-owned plants within a cluster became negative but was still statistically insignificant. This suggests that there were no significant differences in productivity spillovers between FDI and UK-owned investment within the region.

Clusters in the North East where an increase in the presence of foreign-owned plants resulted in positive spillovers are Cluster 33, Plastic and Rubber Products, where the presence of US-owned plants has a positive impact on UK-owned plants' productivity, and Cluster 39, Vehicles where an increased presence of ROW-owned plants has a positive impact on UK-owned plants' productivity. When spillovers were considered alongside employment, Cluster 39, Vehicles, and Cluster 33, Plastic and Rubber Products again emerge as significant for the North East, incorporating both high levels of employment, and positive spillovers. Were the North East to be incorporated into an industrial strategy based either nationally, incorporating the South East region priorities, or tailored for the North of England generically, these key North East Clusters would potentially be overlooked, as they do not feature in the North of England or the South East regional industrial make-up. Furthermore, a national or wider regional industrial strategy for the Vehicle cluster potentially may not fully recognise the positive key role of this cluster within the North East region, leaving it vulnerable to potential rationalisation, with the region not prioritised as a centre of such industries, such as occurred when Sunderland shipbuilding was closed in a wider geographical rationalisation of the industry across Europe. This is further evidence that including the North East in a broader industrial strategy devised to cover the North of England would risk failing to support vital North East interests.

The prominence of Cluster 39, Vehicles potentially reflects the presence of Nissan in the region. Should Nissan therefore choose to leave the region, or become destabilised as a company, the negative consequences for the region would be severe. In policy terms this suggests that policies to retain and support Nissan in the region are vital, but that further diversification from this heavy reliance on not only a single industry, but a single plant from a single company within that industry would increase the region’s resilience in the event of future downturns within the vehicle industry and this specific company.

Differences between the regional economies studied become most apparent when the clusters are ordered by above national average representation of industry clusters in the three comparison regions. The above national average concentrations of clusters across both the South East (Cluster 10, Large Transport Manufacturing, Cluster 37, Synthetic Rubber, Cluster 27, Precision Apparatus, Cluster 29, Essential Oils), and the North of England (Cluster 36, Wall Coverings, Cluster 31, Man Made Fibre Production, Cluster 40, Textiles, Cluster 28, Inorganic and Organic Chemicals), were very different from each other and to those industry clusters vital to the North East. Their relevance, except potentially for Cluster 28, Inorganic and Organic Chemicals, to the North East is minimal, supporting the contention the North East requires its own industrial strategy reflecting its priorities, and supporting its unique industrial base. The Clusters with above national average representation in the North East for both employment and number of plants relate to the exploitation of minerals in the region: Cluster 5, Other Minerals Extraction and Cluster 45, Mining Machinery, as well as Cluster 28, Inorganic and Organic Chemicals. These clusters are strongly related to the unique regional geology, therefore unrepresented in the South East and North of England, meaning that were the North East not to have a bespoke industrial strategy reflecting this specific factor it is possible these industries would be unsupported.

The importance of regional host characteristics is highlighted by estimating the impact of other UK-owned plants within a cluster across the three regions. In every case in the North and North East regions, an increase in the spatial concentration of UK-owned plants had a negative impact on the productivity of UK-owned plants in the same cluster. However, the opposite was true of the South East, where an increase in other UK-owned plants had a positive and significant impact on productivity in UK-owned plants in the same cluster. In the South East, again in contrast with the North East where the opposite was true, FDI had a negative impact on productivity in other UK-owned plants in the same cluster suggesting that FDI in the South East is capitalising on, and benefitting from, positive spillovers from the domestic industries located there and has adequate interlinkages to support itself in a community of high productivity industries. These results reflect the findings in other studies such as Girma and Wakelin (2007), Schiffbauer et al. (2017), Bournakis, Papanastassiou, and Pitelis (2019) and Castellani, Driffield, and Lavoratori (2024), where host region characteristics influence the impact of FDI within a region.

When considering attracting FDI to deliver increased productivity and spillover benefits, the North East's regional characteristics must be considered. Characteristics inhibiting the North East from fully benefitting from positive spillovers today include poor transport links with in the region and nationally, a low skilled workforce with low wages, low land values, and low-tech plants. In order to fully benefit from FDI, the North East needs to consider improving its host region characteristics, through investment in improved transport links, through developing a flexible skilled workforce able to attract high tech manufacturing and command higher wages, and potentially to capitalise on its world class Universities and encourage the location of R&D in the region. The region should insist on these characteristics, which have been demonstrated to result in positive spillovers, being integral to any future investment agreements. Incorporating R&D within the region, long term training opportunities, and contributions to infrastructure as part of the investment package, are essential to avoid the North East region becoming part of a race to the bottom. The North East has been seen as a base for arm's length production facilities, producing low value intermediate supplies, and a region which has largely not seen the promised benefits of sustained production or positive spillovers from investment, and needs to move forward (Benyon and Austrin 1978).

From this comparison it is evident that the North in general, and the North East in particular, require very different bespoke investment strategies from those seen to be effective in the South East. The North East must avoid being incorporated into a national investment strategy based on principles helpful in the South East.

A North East centred industrial strategy should include policies to encourage further US-owned foreign investment in Cluster 33, Plastics and Rubber Products industries because of their positive spillovers. and support for region specific industries relating to mineral extraction. Access to any national support for metal manufacturing, particularly to potentially improve productivity in the North East, and the electronics manufacturing sector should also be sought. FDI, particularly from US-owned and ROW-owned firms is to be encouraged, in preference to that from UK and EU-owned firms, given the impact on supply chain businesses outlined below. Foreign investment proposals should be scrutinised to ensure they are not based on exploiting regional characteristics, such as low wages and land costs, the so called "race to the bottom" features of the region. It should bring value-added finished goods manufacturing, R&D, training opportunities, and investment in regional infrastructure, particularly transport. The North East should attempt to improve its key host region characteristics by improving education levels and transport links within the region and across the wider North and UK.

The UK has both one of the world's most centralised systems of Government, paired with some of the greatest regional inequalities in productivity, the North East being one such area suffering from weak productivity growth in comparison with the South East region. There is now a significant body of OECD research indicating that decentralisation is strongly linked to reduced inequalities in inter-regional productivity (McCann, 2022). This centralisation is reinforced by the UK fiscal system designed around and so supporting the hyper centralised Governance. This creates a strategic risk that the North East is unlikely to have autonomy in creating an Industrial Strategy able to address its investment requirements, and risks having the same investment strategy as the South East imposed upon it by Central Government. Alternatively, the South East, due to its influential position on the production frontier, may feed largely or exclusively into a national Industrial Strategy to which the North East then becomes subject, when the principles of this strategy would be directly opposed to the region's best interests in terms of investment. The election of the North East and Tees Valley Regional Mayors, and Local Authority Mayors for Middlesbrough and North Tyneside, may improve this situation if they are able to work together with local investment bodies, introducing devolution of regional decision making on investments. Such devolution however also needs to be financially supported by changes to the regional funding system if full benefit is to be realised for the North East.

Overall, my results indicate that in the North East, EU-owned plants are the least productive when compared with other ownership types. It could be that EU-owned plants are producing lower value-added goods or are not involved in high value R&D. Mainland Europe is geographically close by, and over the time period this study covers, there was freedom of movement of goods and people between the UK and the wider EU. This would suggest that the North East was used to produce low value intermediate parts which were then sent to mainland Europe, where the higher value manufacturing took place. The lower cost barriers for the EU-owned plants, when compared with US- and ROW-owned plants, may have meant that there was less of an incentive for them to invest in R&D or produce higher value goods within the region.

This potentially suggests that the UK's decision to leave the EU may not affect the North East region as much as previously thought, given the limited positive impact of EU FDI in the region. EU-owned plants were the worst performing ownership group in terms of employment, productivity and positive spillovers, with the presence of EU-owned plants not increasing productivity in the region's UK-owned plants. Their productivity effect has a marginal, if any, impact on the region's productivity.

However, the importance to the region of being part of the EU ranges much wider than this status encouraging inward FDI from countries within the EU. The region also stands to lose capital investment in infrastructure through EU funded projects, and social support in areas such as education and skill development. A major concern would be if all ownership types reduced their presence in the region because of Brexit. A motivation for the different ownership groups to establish within the North East may well have been to use the region as a bridge to access the European Single Market. This was the case with Nissan at the time of their investment. "Nissan had located in Sunderland in 1986 having been persuaded by Mrs Thatcher that the combination of British engineering excellence and tariff free access to the European Union made Britain an ideal location." (Hansard 4th May 2019 Greg Clarke Secretary of State for Business, Energy and Industrial Strategy) The North East was well placed to function in this way to a range of non-EU investors, as it is located on the closest East facing coast with strong shipping links into North West Europe, through deep water ports, accessible via road transport links.

As the UK has now left the EU, there are additional costs and barriers in place impacting on this investment strategy, which could potentially result in these plants choosing to reduce their presence or leave the region entirely. In addition to the loss of the employment and productivity from the removal of the plants themselves, this would increase the proportion of UK-owned plants within the region, and it has been seen that such an increase in the presence of UK-owned plants has a significant detrimental impact on productivity in the other UK-owned plants. Therefore, it is important that steps are taken within the region, as far as possible to retain the existing foreign-owned plants, especially in the key clusters of Cluster 33, Plastic and Rubber Products and Cluster 39, Vehicles.

Since the EU referendum vote, there has been a decline in the number of greenfield FDI projects in all regions of the UK. The number of projects in the North East peaked in 2015, with almost 35 projects; this then dropped to the second lowest in 2016 with less than 10 greenfield projects. Most other regions saw a bounce back in the number of greenfield FDI projects. While there was a slight recovery in the number of projects from 2016 to 2021 in the North East, the number did not return to pre-2016 levels. In terms of value of project, since 2016, the value of the projects in the North East has been one of the lowest, with the exception in 2019 with the announcement of £9bn investment into the Dogger Bank wind farm, benefitting the North East coastal areas and East Yorkshire, and the purchase of Newcastle Football Club in 2021 for £3bn (Driffield et al., 2024a). The Dogger Bank wind farm investment is based upon the unique geographical assets of the region, not available on this scale to other regions. It is potentially concerning that there has been no other investment beyond this in the period since the EU referendum. While the North East may not currently lose its existing positive non-EU FDI, this pattern raises concerns that it may be limited over time in being able to attract future such investment.

This thesis concurs with the findings in the recent series of briefings examining "UK Foreign Investment Position Post-Brexit and COVID" (Driffield et al., 2024b), where it corroborates and expands on the findings in Briefing 4. The authors state that high productivity FDI is concentrated in areas and regions where high productivity FDI already exists. Likewise, low productivity FDI is attracted to areas and regions with pre-existing low productivity FDI, due to such established factors as the availability of low waged labour and land costs associated with those regions.

Briefing 4 further states the necessity for more granular research to underpin policy decisions designed to both increase productivity and employment opportunities as part of any “levelling up” strategy. This thesis represents the early stages of such granular research and provides the analytical research method on which to take this forward.

Limitations with this work include the use of System GMM which can result in the over-fit of endogenous variables through the rapid increase in the number of instruments relative to the sample size used (Roodman, 2009). This can skew the coefficients toward the non-instrumented estimators. Further limitations occur in the creation of the cluster configurations. The decision to use SIC 1980 means that the industry classification is more aggregated when compared to the industry classification used by Delgado (2016). This can prevent additional inter-industry linkages from being defined. As this configuration is then used to estimate the spatial concentration of foreign-owned firms, there is the possibility that these linkages are either over or under stated, skewing the estimated impact of spatial concentration on productivity. The decision to use this aggregation was due to the limitations within the data sets. The earlier years of the time period were missing the SIC 1980 classification, meaning the thesis would be unable to cover the impact of the announcement and introduction of the EU single market. Additionally, there is no information available on firm-to-firm linkages for the UK manufacturing sector, something which handicaps all research in this area, and which would have greatly improved the cluster definitions.

I have treated foreign ownership and the co-location indices with foreign firms as exogenous. However, there is a potential risk that these variables are endogenous. This would imply that the estimate effects in this thesis may be biased. However due to the lack of a credible instrumental variable within the dataset, this is the most appropriate method. Although the findings need to be viewed in the light of this weakness, within my research framework, the method chosen remains the most reliable available.

This work can be expanded upon in future analysis in several ways. FDI as analysed in “UK Foreign Investment Position Post-Brexit and COVID” (Driffield et al., 2024b) is shown to generate either high productivity through highly productive FDI, or higher employment, from the less productive FDI. This is a key dilemma for policy makers in regions such as the North East, where generating employment at scale is politically a main driver. Using the cluster method devised in this thesis, it is possible to expand the analysis, looking at the impacts of FDI in multiple regions, and thus create a comparable

UK wide granular region-based data base. This would identify for policy makers those clusters delivering both high levels of employment and productivity, such as Cluster 39, Vehicles. This could inform FDI decisions on a national basis and facilitate the best regional balance of bespoke productive investments, addressing both employment and productivity.

This work could be made more accurate and contemporary by repeating the process using more up-to-date data, for example by including data from 2014 to 2019. Beyond 2019, it is difficult to disentangle the Brexit effect from other world events such as the COVID-19 pandemic and the energy price increases (OBR, 2024; Bolton & Stewart, 2024). However, it would be useful to consider the impact of these world events in future research, attempting to separate out the timescales and so address their varying impacts. The analysis could be repeated with updated clusters using more granular and updated SIC classifications. This would capture the finer linkages between industries and provide a more comprehensive and accurate cluster configuration. A later start to the time period studied is likely to be needed to accommodate the missing values for the earlier years. Further, the clusters could be recalculated using both manufacturing and services sectors, as was originally seen in the work by Delgado et al (2016). This would provide a more comprehensive network of inter industry linkages and provide much more realistic cluster configurations. Furthermore, consideration could be given to including labour characteristics, such as educational level and wage level within the cluster configuration.

Finally, this work could be expanded to not only examine the impact of foreign-owned plants within clusters but also the impact of foreign-owned plants between clusters, similar to as Girma and Wakelin (2002) and Haskel et al (2007). As it can be assumed that a region will not be home to a single cluster, there will be additional linkages between clusters which this work does not capture. This work could additionally be expanded beyond examining the impact of foreign ownership to include examining the impact of technologically advanced plants within and between clusters.

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Appendix

A.1 Driffield and Love (2007) taxonomy on FDI

This is a more comprehensive explanation of the taxonomy discussed in the Chapter 3.

	ULC host < ULC Source	ULC Host > ULC Source
RDI host > RDI Source	(1) Technology Sourcing/location advantage	(2) Technology Sourcing
RDI host < RDI Source	(3) Ownership advantage/ efficiency seeking	(4) Ownership advantage

Table A1-1 Driffield and Love Taxonomy (2007)

In the taxonomy, technology is measured by R&D intensity (RDI) and costs are measured in terms of unit labour costs (UCL). This model can be applied to the firm level as well as the national level. The top row focuses on whether the foreign firm has technology sourcing motive.

(1) The host economy has a great level of RDI and a lower UCL then the Source investor. Therefore, the inward investment is technology sourcing, with the aim to take advantage of hosts lower UCL. This would result in no or a negative spillover effect, as these firms may lag behind in technology and may choose to compete on labour costs, rather than technology efficiencies

(2) The source investor is attracted to the host economy due to its higher RDI, and is not deterred by the higher UCL in the host economy. There would be no expected spillover effect from this type of investment, as they would have nothing to offer the host economy due to their level of technology being less advanced

The bottom row has ownership advantage as the source firm's main motivation for investing in the host economy

(3) The host has low labour costs, and the source investor has a greater RDI, which could suggest these investors are efficiency seeking. With this scenario, there is a small positive spillover effect predicted, due to the superior technology, but as there are low labour costs, firms may still choose to compete on this rather than improve technology efficiency

(4) The source investor has a greater level of RDI than the host economy, FDI is still happening even with the hosts great UCL. This scenario would result in the highest level of positive spillovers due to the higher level of RDI from the source investor.

This model is very limited, there are other reasons why a foreign firm may wish to set up in a host economy, however it is a simple way in showing foreign firms motivation to move into a host economy.

A.2 Estimation Methodologies

Productivity can be estimated using a variety of techniques, both non-parametric and parametric methodologies can be used. Both methodologies have benefits, from simple configurations to overcoming endogeneity within variables. However, both have weaknesses, such as being significantly impacted by measurement errors to sacrificing precision for flexibility.

A.2.1 Non-parametric Methodologies

Non-parametric methodologies are suitable for small sample sizes, does not require the data to have a normal distribution, and focuses more on the medians rather than means (Scheff, 2016). This methodology examines, or compares, the rank sums rather than the value of the individual observations *(Flint, 2021)*. Non-parametric approaches also are not limited by functional misspecification, something that parametric approach can suffer from (Porcelli, 2009).

Index numbers methodology was developed by Caves, Christensen and Diewert (1982) in order to make straight forward comparisons between units, such as plants, firms or countries. They adapted Malmquist approach[58] allow discrete changes in inputs, outputs and the structure of production. The technique can handle multiple outputs and inputs and does not require any estimation in its computation. It has strict assumptions that all firms are minimising cost, and the good marketing are competitive, provides an exact measure of productivity without the need to estimate a full range of input substitutions. However, the approach is deterministic is also one of the main disadvantages of the approach. Even though deterministic models can suggest the influence of certain parameters on the variable of interest, they do not account for unknowns within the data (Renard et al., 2013). The inputs and outputs used to compute productivity need to be known in their entirety in order to have an accurate picture.

Data Envelopment Analysis (DEA) is a nonparametric frontier estimation that measures the efficiency of decision-making units (DMUs). It measures efficiency as a proportional change in input-outputs and allows for multiple input-outputs to be used simultaneously without having to impose assumptions on data distribution (Ji & Lee, 2010). The method does not require a production function, instead a ratio is used to defined productivity (Van Biesebroeck, 2008).

Charnes, Cooper and Rhodes (1978) initially developed DEA where efficiency was measured assuming constant returns to scale and that all DMUs operated at their optimal scale. However Banker, Charnes and Cooper (1984) adapted the original to include variable returns to scale, enabling the breakdown of efficiency into technical and scale efficiencies (Ji & Lee, 2010). For each observation, a linear ratio is calculated using inputs and outputs that would maximise efficiency or productivity for that observation. Each of these calculations can be consolidated to form a frontier. This analysis does not require any functional form or behavioural assumptions, allowing for technology to vary across DMUs (Van Biesebroeck, 2008). A DMU is defined as dominant when it produces more outputs using the same amount of aggregated inputs, using the same weights (Van Biesebroeck, 2008). Those DMUs

[58] This approach suggests comparing the inputs and outputs of a firm at two different points in time however there are limitations to this, such as changes in firms' structure and consumer preferences are excluded Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The Economic Theory of Index Numbers and the Measurement of Input, Output, and
Productivity. *Econometrica*, *50*(6), 1393-1414.

which are not dominant are labelled as 100% efficient, this is one of the limitations of this model as the likelihood of this being true in all cases is very low. Measurement errors also can have a large impact on all productivity estimates due to the fact each observation is compared with all other observation in the dataset, a mistake with a single observation could affect the overall results (Van Biesebroeck, 2008). Again, this is not a stochastic estimation, therefore, makes it susceptible to outliers within the data (von Hirschhausen et al., 2006).

The main disadvantage with non-parametric techniques is their deterministic nature and being non-stochastic. This means that estimates can be affected by statistical noise, possible measurement errors, and possible omitted variables. To overcome some of these problems, using parametric techniques allows for the inclusion of statical noise in the model (Porcelli, 2009).

A.2.2 Parametric Methodologies

Parametric tests differ to non-parametric tests as they require data to be normally distributed and focus on mean rather than the median. It is argued that parametric methodologies are stronger than non-parametric tests (Chin & Lee, 2008), as non-parametric tests have a tendency to be less robust (DePoy & Gitlin, 2016). When using parametric tests to estimate productivity, the stochastic framework makes the estimates less susceptible to measurement errors due to the assumption that all the heterogeneity being focused on the productivity term (Van Biesebroeck 2008). These tests can address the problem of endogeneity within the chosen input parameters.

The Stochastic frontier, proposed by Aigner et al (1977) and Meeusen and van den Broeck (1977), is a model based upon the assumption that the unobserved productivity component can be separated from the error term using the distribution of that component (von Hirschhausen et al., 2006). This approach has the ability to incorporate measurement error and any statistical noise (Ondrich & Ruggiero, 2001). The model allows for technical inefficiency as well as allowing for random shocks to impact upon output and for different impacts to be separated from variation in technical efficiency (Kumbhakar & Lovell, 2000). The deterministic components of the production function can be generated easily, allowing for more sophisticated specifications. This approach does have its disadvantages, it trades flexibility in its specification with estimation precision as well as requiring a large amount information to being with, such as the specification of production function and the distribution of each error component (Ondrich & Ruggiero, 2001). Some argue the usefulness of this technique with this lack of precision and its inability to generate reliable estimations of efficiency (Ondrich & Ruggiero, 2001). Another disadvantage is the failure to correctly specify the deterministic component due to missing inputs or measurement errors within the inputs. An obvious way to overcome this is to collect better quality data, however that is not always possible, therefore instrumental variables need to be used for the endogenous inputs (Porecelli, 2009).

Olley and Pakes (1996) developed a method to estimate productivity, using a semiparametric estimation. The nonparametrically inverted investment term[59] becomes the observable expression of the productivity term. The estimation is a two-step process. The first step estimates the input coefficients and the joint effect of all state variables. The second step identifies the observable state variables- in this case it would be capital. There is an additional step which can control for sample selection. This method allows for the flexible classification of productivity due to it following the Markov process and is not affected by the control variables. However, the nonparametric element of

[59] The investment term is included in the capital stock with a one period lag.

this estimation where the inverted functions need to hold for all firms, regardless of firm's characteristics (Van Biesebroeck 2008). Also, the assumptions used to the identify the input coefficients can be restrictive (Ackerberg et al., 2015). Levinsohn and Petrin (2003) built upon this method, and included intermediates to overcome the simultaneity problem that Olley and Pakes use investment to control for.

Another parametric estimation technique uses instrumental variables. Developed by Blundell and Bond (1998), Generalised Method of Moments (GMM) is a standard first-differenced estimator that can be used to estimate dynamic error component models. The standard GMM estimation method requires the data to be first differenced to remove the fixed effects. The first differences would then be estimated (Roodman, 2009). There are issues with this method. If there are fixed effects persistent then the differenced GMM would become biased and imprecise due to the instruments being weak. These variables become less informative due to the number of times the data would have to be differenced to remove the fixed effects. A solution is to use System GMM, which estimates in both differences and levels equations simultaneously (Roodman, 2009). The model has better finite sample properties, is flexible when generating instruments, and remains a good predictor of variables even if they are very persistent as well as overcome the presence of endogenous variables (Blundell & Bond, 1998). However, due to two equations being estimated simultaneously, the number of instruments can increase rapidly relative to the sample size. This can result in the over-fit of endogenous variables, biasing coefficients towards the non-instrumented estimators (Roodman, 2009). This model does require a number of time periods, and it does risk the coefficients being underestimated, especially if instruments are weak.

A.2.3 Methodologies in the literature

There have been a number of papers in the literature that have compared the results of parametric and non-parametric estimation techniques. Casu, Girardone and Molyneux (2004) compared productivity in European banking sector using parametric and non-parametric techniques. They found that both methods consistent in identifying the systems that had benefitted the most or least from productivity change in the 1990s. Graham (2008) compared both parametric and non-parametric efficiency scores in regard to productivity and efficiency in urban railways. They concluded that the type of estimation used is dependent upon the availability of data rather than any particular analytical merit. Parametric methods are better suited for data that is over cross-sectional units or over time. It can provide better estimates relating to factor inputs and provide statistical verification of parameters. Whereas Non-Parametric methods are better for when the variance in the data is poor. Huang and Wang (2002) found that non-parametric and parametric methods produce similar average efficiency estimates, yet on a more granular scale the results do differ. This is echoed by Czekaj and Henningsen (2012) who found, on average, non-parametric estimates deliver similar results as parametric results, but the individual results differ considerably. Huang and Wang (2002) suggest combining both methods to help support policy decisions and evaluations. However, Murilli and Vega (DATE) state that does this means that the methodological issues present in both techniques will be present in the final estimates.

A.3 Regional Descriptive statistics

A.3.1 Average number of plants across all regions

AVERAGE NUMBER OF PLANTS	UK	EU	US	ROW	TOTAL
NATIONAL	159,213	2,593	1,941	878	164,625
NORTH EAST	4,632	120	90	46	4,886
NORTH OF ENGLAND	24,658	597	456	231	25,010
SOUTH EAST	22,277	333	313	113	23,036

Table A3-1 Average number of plants across all regions and years

A.3.2 Average level of employment across all regions

AVERAGE EMPLOYMENT	UK	EU	US	ROW	TOTAL
NATIONAL	2,953,560	273,481	315,903	113,454	3,656,398
NORTH EAST	121,308	16,159	13,705	10,487	161,322
NORTH OF ENGLAND	566,969	65,603	66,842	29,060	675,164
SOUTH EAST	318,462	30,195	44,511	8,710	401,878

Table A3-2 Average level of employment across all regions and years

A.4 Regression output tables for the ownership effect on productivity

A.4.1 Output results for foreign ownership effects in the North East of England

VARIABLES	(1)	(2)	(3)	(4)
INTERMEDIATE INPUTS	0.570***	0.571***	0.549***	0.548***
	(11.25)	(10.92)	(10.07)	(9.616)
EMPLOYMENT	0.490***	0.485***	0.444***	0.436***
	(7.691)	(7.618)	(7.321)	(7.081)
CAPITAL	0.0813*	0.0879*	0.109*	0.126**
	(1.670)	(1.771)	(1.796)	(2.048)
AGE	-0.146***	-0.15***	-0.186**	-0.201***
	(-2.431)	(-2.503)	(-2.336)	(-2.562)
MULTI SIC	-0.0179	-0.0179	-0.00622	-0.00911
	(-0.842)	(-0.845)	(-0.252)	(-0.365)
MULTI REGION	0.0707***	0.0681***	0.0920***	0.0890***
	(2.478)	(2.341)	(3.053)	(2.851)
SINGLE	-0.0815***	-0.0817***	-0.0341	-0.0375
	(-2.628)	(-2.544)	(-1.055)	(-1.103)
HERFINDAHL	0.266***	0.261***	0.210**	0.209**
	(2.683)	(2.603)	(2.158)	(2.072)
NE FO	0.0352	0.0351	-	-
	(1.573)	(1.570)	-	-
NE EU	-	-	0.0129	0.00940
	-	-	(0.389)	(0.282)
NE ROW	-	-	0.0730**	0.0721**
	-	-	(2.212)	(2.061)
NE US	-	-	0.0747**	0.0705**
	-	-	(2.572)	(2.408)
MIDDLESBROUGH	-	0.0148	-	0.000730
	-	(0.649)	-	(0.0335)
NEWCASTLE	-	0.0175	-	0.0238
	-	(0.699)	-	(0.953)
SUNDERLAND	-	0.0568***	-	0.0595**
	-	(2.177)	-	(2.357)
SIC 23	-0.0825	-0.0765	-0.175**	-0.171*
	(-0.812)	(-0.731)	(-2.026)	(-1.888)
SIC 24	0.366***	0.374***	0.257***	0.272***
	(4.059)	(3.970)	(2.924)	(2.937)
SIC 25	0.214***	0.215***	0.165***	0.166***
	(3.476)	(3.416)	(3.040)	(2.904)
SIC 26	0.151	0.169*	0.0981	0.124
	(1.600)	(1.696)	(1.134)	(1.293)
SIC 31	0.205***	0.216***	0.162*	0.186*

	(2.534)	(2.600)	(1.737)	(1.959)
SIC 32	0.255***	0.262***	0.205**	0.226**
	(3.210)	(3.232)	(2.156)	(2.349)
SIC 33	0.135	0.135	-0.0163	-0.00522
	(1.188)	(1.164)	(-0.139)	(-0.0418)
SIC 34	0.0194	0.0293	-0.00125	0.0131
	(0.296)	(0.434)	(-0.0186)	(0.188)
SIC 35	0.119	0.124	0.0493	0.0654
	(1.633)	(1.634)	(0.655)	(0.823)
SIC 36	0.0977	0.110	0.0490	0.0736
	(0.913)	(1.015)	(0.423)	(0.626)
SIC 37	0.238**	0.241**	0.153	0.167
	(2.397)	(2.382)	(1.453)	(1.537)
SIC 41	-0.0390	-0.0239	-0.0948	-0.0649
	(-0.485)	(-0.289)	(-1.049)	(-0.703)
SIC 42	0.252***	0.258***	0.208***	0.219***
	(3.950)	(3.906)	(3.202)	(3.236)
SIC 43	0.109	0.118	0.0373	0.0606
	(1.075)	(1.136)	(0.341)	(0.545)
SIC 44	0.185	0.204	0.184	0.227
	(1.187)	(1.306)	(1.102)	(1.336)
SIC 45	-0.0150	0.00194	-0.0225	0.0138
	(-0.155)	(0.0198)	(-0.190)	(0.116)
SIC 46	0.0989	0.113	0.0439	0.0720
	(1.169)	(1.282)	(0.458)	(0.724)
SIC 47	0.241***	0.253***	0.156*	0.175**
	(3.104)	(3.117)	(1.937)	(2.099)
SIC 48	0.0876	0.0917	0.0565	0.0676
	(1.376)	(1.391)	(0.898)	(1.027)
SIC 49	0.183**	0.192**	0.138	0.158*
	(2.105)	(2.205)	(1.443)	(1.677)
1986	-0.0309*	-0.0318*	-0.0261*	-0.0274*
	(-1.752)	(-1.790)	(-1.820)	(-1.850)
1987	-0.0623***	-0.0652***	-0.0320	-0.0358*
	(-2.767)	(-2.831)	(-1.592)	(-1.693)
1988	-0.0324	-0.0354	-0.00500	-0.00749
	(-1.334)	(-1.429)	(-0.233)	(-0.332)
1989	-0.00605	-0.0104	0.0194	0.0157
	(-0.257)	(-0.431)	(0.842)	(0.654)
1990	-0.0354	-0.0392	-0.00624	-0.00971
	(-1.491)	(-1.622)	(-0.281)	(-0.421)
1991	-0.123***	-0.128***	-0.0742***	-0.0814***
	(-3.968)	(-4.056)	(-2.710)	(-2.848)
1992	-0.102***	-0.107***	-0.0546*	-0.0623*
	(-3.473)	(-3.533)	(-1.792)	(-1.895)

1993	-0.0683**	-0.0727**	-0.0523	-0.0554
	(-2.131)	(-2.206)	(-1.526)	(-1.533)
1994	-0.0550	-0.0586	-0.0186	-0.0232
	(-1.551)	(-1.618)	(-0.508)	(-0.611)
1995	0.0145	0.0110	0.0324	0.0269
	(0.446)	(0.337)	(0.990)	(0.793)
1996	0.0906***	0.0873***	0.115***	0.112***
	(2.663)	(2.561)	(3.238)	(3.057)
1997	-0.00477	-0.00295	0.0173	0.0220
	(-0.110)	(-0.0677)	(0.408)	(0.502)
1998	-0.0222	-0.0275	0.00864	0.00226
	(-0.562)	(-0.697)	(0.213)	(0.0534)
1999	-0.152***	-0.154***	-0.0832**	-0.0871**
	(-4.169)	(-4.136)	(-2.314)	(-2.300)
2000	-0.116***	-0.12***	-0.0656	-0.0745*
	(-2.891)	(-2.968)	(-1.561)	(-1.724)
2001	-0.116***	-0.12***	-0.0627*	-0.0696*
	(-3.136)	(-3.179)	(-1.733)	(-1.872)
2002	-0.0446	-0.0491	0.00394	-0.00262
	(-1.078)	(-1.157)	(0.0921)	(-0.0593)
2003	-0.0922**	-0.0959**	-0.0340	-0.0390
	(-2.293)	(-2.315)	(-0.824)	(-0.912)
2004	-0.164**	-0.172**	-0.0322	-0.0429
	(-2.123)	(-2.165)	(-0.423)	(-0.542)
2005	-0.0415	-0.0468	-0.0151	-0.0217
	(-0.868)	(-0.964)	(-0.313)	(-0.438)
2006	0.0232	0.0179	0.0493	0.0408
	(0.606)	(0.462)	(1.269)	(1.024)
2007	0.12*	0.116*	0.0882	0.0906
	(1.840)	(1.770)	(1.391)	(1.413)
2008	0.115*	0.115*	0.149**	0.146**
	(1.836)	(1.824)	(2.532)	(2.410)
2009	0.0565	0.0581	0.109*	0.112**
	(0.942)	(0.971)	(1.937)	(1.967)
2010	0.202***	0.205***	0.185***	0.193***
	(3.300)	(3.252)	(2.956)	(2.907)
2011	0.1**	0.0965**	0.116***	0.114***
	(2.411)	(2.285)	(2.794)	(2.602)
2012	0.211***	0.212***	0.225***	0.228***
	(2.984)	(2.984)	(3.720)	(3.684)
2013	0.222***	0.223***	0.256***	0.251***
	(3.302)	(3.267)	(4.173)	(3.903)
2014	0.224***	0.224***	0.239***	0.240***
	(3.709)	(3.656)	(3.921)	(3.779)

CONSTANT	-0.800***	-0.787***	-0.667*	-0.608*
	(0.277)	(0.276)	(0.361)	(0.360)
OBSERVATIONS	9,390	9,390	9,390	9,390
NUMBER OF CSO_REF	2,117	2,117	2,117	2,117
AR(1) Z-STATISTIC	-3.190	-3.188	-1.609	-1.558
AR(1) Z-STATISTIC P-VALUE	0.00142	0.00143	0.108	0.119
AR(2) Z-STATISTIC	-0.281	-0.260	-1.178	-1.199
AR(2) Z-STATISTIC P-VALUE	0.779	0.795	0.239	0.231
HANSEN TEST	31.58	31.09	22.08	21.90
HANSEN TEST P-VALUE	0.109	0.121	0.106	0.110
STANDARD ERRORS IN PARENTHESES *** P<0.01, ** P<0.05, * P<0.1				

Table A.4-1 Output results for foreign ownership effects in the North East of England

A.4.2 Output results for foreign ownership interacted with industry dummies in the North East of England

VARIABLES	(1)	(2)		
INTERMEDIATE INPUTS	0.666***	0.564***		
	(14.48)	(3.479)		
EMPLOYMENT	0.400***	0.124		
	(7.201)	(1.005)		
CAPITAL	0.0993*	0.228*		
	(1.889)	(1.790)		
AGE	-0.171***	-0.171**		
	(-2.539)	(-2.539)		
MULTI SIC	-0.0267	-0.0267		
	(-1.018)	(-1.018)		
MULTI REGION	0.0795***	0.0795***		
	(2.941)	(2.941)		
SINGLE	-0.0590*	-0.059*		
	(-1.692)	(-1.692)		
HERFINDAHL	0.147	0.147		
	(1.340)	(1.340)		
INDUSTRY INTERACTION	FO	EU	ROW	US
SIC 23	-0.0852	*	*	*
	(-0.731)			
SIC 24	0.0838	-0.513*	0.507	0.336
	(1.561)	(-1.736)	(1.356)	(1.372)
SIC 25	-0.00961	0.477	-0.598	-0.427
	(-0.158)	(0.749)	(-1.460)	(-1.241)
SIC 31	-0.00760	0.500	-0.231	0.0917
	(-0.111)	(0.929)	(-0.662)	(0.472)
SIC 32	0.0485	0.204	-0.127	22.72
	(1.087)	(0.524)	(-0.241)	(0.933)
SIC 33	0.206**	4.837	-	*
	(1.981)	(1.262)		
SIC 34	-0.155*	1.118	0.170	0.434
	(-1.649)	(1.232)	(0.495)	(1.382)
SIC 35	-0.0784	1.356	0.364	3.64**
	(-1.372)	(1.223)	(1.218)	(1.966)
SIC 36	0.0383	0.373	*	-
	(0.430)	(0.654)		
SIC 37	-0.254**	-1.145	-	-0.114
	(-2.021)	(-0.633)		(-0.336)
SIC 41	-0.237***	0.0472	-	0.279
	(-3.115)	(0.147)		(0.995)
SIC 42	-0.0252	1.034	*	0.539
	(-0.245)	(1.681)		(1.498)

SIC 43	-0.00466	*	-	*
	(-0.0168)			
SIC 46	-0.146***	0.182	*	-1.869
	(-3.475)	(0.522)		(-1.666)
SIC 47	0.186***	0.219	-0.232**	0.371**
	(3.394)	(0.455)	(2.076)	(2.076)
SIC 48	-0.153***	0.133	0.309	0.143
	(-2.600)	(0.658)	(0.968)	(0.522)
SIC 49	-0.00417	*	*	-3.524
	(-0.0528)			(-0.314)
SIC DUMMIES				
SIC 23	-0.165	0.026		
	(-1.73)	(0.15)		
SIC 24	0.22	0.206		
	(2.88)***	(2.23)**		
SIC 25	0.0004	0.167		
	(0.05)	(1.63)		
SIC 26	-0.032	0.045		
	(-0.28)	(0.38)		
SIC 31	0.149	0.001		
	(2.16)**	(0.02)		
SIC 32	0.201	0.024		
	(2.84)***	(0.31)		
SIC 33	0.342	0.134		
	(2.16)**	(0.63)		
SIC 34	0.034	-0.066		
	(0.50)	(-0.87)		
SIC 35	0.069	-0.024		
	(1.08)	(-0.36)		
SIC 36	0.103	-0.063		
	(1.01)	(-0.58)		
SIC 37	0.164	-0.05		
	(1.76)*	(-0.47)		
SIC 41	-0.052	-0.279		
	(-0.58)	(-2.60)***		
SIC 42	0.131	0.103		
	(2.32)**	(1.70)*		
SIC 43	0.019	-0.118		
	(0.24)	(-1.44)		
SIC 44	-0.216	-0.658		
	(-0.49)	(-1.32)		
SIC 45	-0.009	-0.327		
	(-0.07)	(-2.15**)		
SIC 46	0.04	-0.13		

	(0.52)	(1.63)
SIC 47	0.132	0.012
	(1.81)*	(0.15)
SIC 48	0.132	-0.075
	(-0.21)	(-1.34)
SIC 49	-0.012	-0.052
	(1.93)*	(-0.47)
1986	-0.0348*	-0.0819
	(-1.705)	(-0.503)
1987	-0.0797***	-0.0602
	(-3.164)	(-0.438)
1988	-0.0439*	-0.0240
	(-1.723)	(-0.143)
1989	-0.00866	0.190
	(-0.359)	(0.928)
1990	-0.0414*	-0.113
	(-1.654)	(-0.773)
1991	-0.124 ***	-0.480
	(-4.098)	(-1.853)
1992	-0.0963***	-0.0913
	(-3.326)	(-0.446)
1993	-0.0792***	0.327
	(-2.622)	(1.188)
1994	-0.0793**	0.641
	(-2.393)	(1.667)
1995	-0.0184	0.511
	(-0.587)	(1.543)
1996	0.0617*	0.591
	(1.795)	(1.500)
1997	-0.0108	-0.696
	(-0.211)	(-1.762)
1998	-0.0489	0.0430
	(-1.205)	(0.124)
1999	-0.19***	-0.209
	(-5.301)	(-1.068)
2000	-0.174***	0.284
	(-4.665)	(1.030)
2001	-0.171***	-0.255
	(-4.881)	(-1.347)
2002	-0.0929**	0.273
	(-2.409)	(1.009)
2003	-0.147***	-0.0133
	(-3.888)	(-0.0669)
2004	-0.221***	0.574

	(-3.153)	(1.053)
2005	-0.0848*	0.912
	(-1.935)	(1.428)
2006	-0.00367	0.553
	(-0.0978)	(1.475)
2007	0.106	-0.862
	(1.332)	(-1.464)
2008	0.0854	0.489
	(1.431)	(1.223)
2009	0.00419	-0.00432
	(0.0621)	(-0.0108)
2010	0.199***	0.648
	(2.957)	(1.457)
2011	0.0774*	0.0508
	(1.923)	(0.202)
2012	0.180**	0.188
	(2.262)	(0.505)
2013	0.200***	0.124
	(2.855)	(0.357)
2014	0.194***	-0.0697
	(3.190)	(-0.241)
CONSTANT	-0.243	0.122*
	(0.230)	(0.063)
OBSERVATIONS	9,390	9,390
NUMBER OF CSO_REF	2,117	2,117
AR(1) Z-STATISTIC	-3.481	-4.052
AR(1) Z-STATISTIC P-VALUE	0.000499	5.08e-05
AR(2) Z-STATISTIC	-0.000593	2.333
AR(2) Z-STATISTIC P-VALUE	1	0.0197
HANSEN TEST	42.86	37.27
HANSEN TEST P-VALUE	0.0763	0.365

STANDARD ERRORS IN PARENTHESES *** P<0.01, ** P<0.05, * P<0.1

Table A.4 -2 Output results for foreign ownership interacted with industry dummies in the North East of England

A.4.3 The foreign ownership effect in the South East and North of England

VARIABLES	(1) SE	(2) SE	(3) NORTH	(4) NORTH
INTERMEDIATE INPUTS	0.627***	0.629***	0.572***	0.575***
	(9.018)	(9.538)	(7.100)	(10.39)
EMPLOYMENT	0.315***	0.318***	0.388***	0.427***
	(3.384)	(3.879)	(4.056)	(6.384)
CAPITAL	0.208*	0.195**	0.140*	0.0673*
	(1.839)	(2.027)	(1.774)	(1.701)
AGE	-0.269*	-0.236*	-0.198**	-0.175***
	(-1.867)	(-1.876)	(-1.780)	(-3.368)
MULTI SIC	-0.044**	-0.042**	0.00956	0.0244**
	(-2.159)	(-2.229)	(0.481)	(2.140)
MULTI REGION	0.0542*	0.0578**	0.0458	0.0553**
	(1.938)	(2.293)	(1.449)	(2.497)
SINGLE	0.0131	0.00988	-0.0116	0.00833
	(0.425)	(0.364)	(-0.443)	(0.498)
HERFINDAHL	0.126*	0.115	0.192*	0.187**
	(1.658)	(1.552)	(1.894)	(2.402)
FO OWNED	-0.0242		0.0224	
	(-0.684)		(0.561)	
EU OWNED		-0.0743**		0.0226
		(-2.001)		(0.795)
ROW OWNED		0.00823		0.00749
		(0.155)		(0.220)
US OWNED		0.0393		0.0728***
		(1.035)		(3.075)
SIC 23	0.375***	0.387***	0.151*	0.169***
	(3.240)	(3.816)	(1.897)	(2.696)
SIC 24	0.221**	0.230**	0.199***	0.194***
	(2.135)	(2.382)	(3.260)	(4.278)
SIC 25	0.0131	0.0101	0.130**	0.147***
	(0.177)	(0.143)	(2.467)	(3.546)
SIC 26	-	-	0.00565	0.00838
			(0.0697)	(0.235)
SIC 31	0.283***	0.280***	0.130**	0.0675*
	(2.675)	(2.673)	(1.962)	(1.791)
SIC 32	0.288***	0.283***	0.203**	0.114***
	(2.861)	(2.886)	(2.422)	(2.581)
SIC 33	0.0408	0.0543	-0.0605	-0.146
	(0.188)	(0.253)	(-0.408)	(-0.915)
SIC 34	0.105	0.107	0.0634	-0.00415
	(1.402)	(1.407)	(1.155)	(-0.120)

SIC 35	0.112	0.110	0.126**	0.0554
	(1.256)	(1.286)	(2.089)	(1.575)
SIC 36	0.204*	0.196**	0.126*	0.0571
	(1.946)	(2.031)	(1.599)	(1.262)
SIC 37	0.126*	0.131**	0.146*	0.103**
	(1.951)	(1.986)	(1.949)	(2.126)
SIC 41	0.0634	0.0593	-0.0385	-0.136**
	(0.844)	(0.772)	(-0.447)	(-2.535)
SIC 42	0.102	0.108	0.173***	0.173***
	(1.172)	(1.245)	(4.682)	(5.065)
SIC 43	0.117	0.0991	0.00749	-0.0344
	(0.955)	(0.762)	(0.158)	(-1.058)
SIC 44	0.0668	0.0654	0.0746	0.0729
	(0.502)	(0.599)	(0.646)	(0.738)
SIC 45	0.277	0.265	0.0183	-0.103
	(1.485)	(1.534)	(0.136)	(-1.349)
SIC 46	0.209*	0.208*	0.0796	-0.00332
	(1.725)	(1.797)	(1.025)	(-0.0814)
SIC 47	0.236***	0.236***	0.177***	0.137***
	(3.088)	(3.035)	(2.672)	(3.216)
SIC 48	0.113	0.113	0.0792*	0.0350
	(1.436)	(1.437)	(1.772)	(1.247)
SIC 49	0.216**	0.208**	0.126*	0.0581
	(2.426)	(2.439)	(1.679)	(1.252)
1986	-0.00812	-0.0105	0.000938	0.00126
	(-0.469)	(-0.588)	(0.0708)	(0.140)
1987	-0.0354*	-0.0353*	-0.00482	0.00648
	(-1.891)	(-1.873)	(-0.289)	(0.635)
1988	0.00295	-0.000369	0.00392	0.0210
	(0.140)	(-0.0171)	(0.174)	(1.475)
1989	-0.0240	-0.0285	0.00729	0.0392
	(-0.940)	(-1.189)	(0.255)	(1.967**)
1990	-0.0222	-0.0216	0.00962	0.0221
	(-0.912)	(-0.925)	(0.470)	(1.505)
1991	-0.0617**	-0.0603**	-0.0143	-0.00165
	(-2.513)	(-2.518)	(-0.644)	(-0.106)
1992	-0.0715***	-0.0723***	-0.0153	0.00419
	(-2.901)	(-2.995)	(-0.556)	(0.201)
1993	-0.0388	-0.0375	-0.00131	0.00837
	(-1.496)	(-1.403)	(-0.0351)	(0.320)
1994	0.00532	0.00773	0.0431	0.0610*
	(0.169)	(0.238)	(0.859)	(1.821)
1995	0.00241	0.00342	0.0299	0.0660**
	(0.0532)	(0.0787)	(0.723)	(2.324)
1996	0.0828*	0.074*	0.0567**	0.0891***

	(1.918)	(1.893)	(2.001)	(4.304)
1997	-0.0201	-0.0215	0.0121	0.0445
	(-0.408)	(-0.426)	(0.358)	(1.573)
1998	0.0426	0.0474	-0.0260	-9.91e-05
	(0.991)	(1.187)	(-0.779)	(-0.00469)
1999	-0.113**	-0.116***	-0.0787	0.00620
	(-2.450)	(-2.661)	(-1.237)	(0.147)
2000	-0.0403	-0.0358	-0.0425	-0.0109
	(-0.813)	(-0.838)	(-0.937)	(-0.373)
2001	-0.0616	-0.0554	-0.0262	-0.00494
	(-1.304)	(-1.235)	(-0.635)	(-0.186)
2002	-0.0834*	-0.0728	-0.0174	0.0370
	(-1.726)	(-1.501)	(-0.325)	(0.982)
2003	-0.0653	-0.0570	-0.0255	0.0123
	(-1.372)	(-1.210)	(-0.516)	(0.362)
2004	-0.135**	-0.133**	-0.14**	-0.0580
	(-2.142)	(-2.375)	(-2.382)	(-1.463)
2005	0.0144	0.0206	0.0618	0.0549
	(0.299)	(0.418)	(1.568)	(1.513)
2006	0.0490	0.0520	0.0692*	0.0932***
	(0.995)	(1.065)	(1.737)	(3.165)
2007	0.157**	0.128*	0.172***	0.150***
	(2.035)	(1.737)	(2.790)	(3.635)
2008	0.168**	0.169**	0.115**	0.114***
	(2.490)	(2.484)	(2.268)	(3.225)
2009	0.249***	0.270***	0.259***	0.171***
	(3.899)	(4.405)	(4.305)	(4.106)
2010	0.222***	0.212***	0.208***	0.228***
	(3.003)	(3.226)	(3.641)	(5.769)
2011	0.264***	0.263***	0.199***	0.196***
	(3.484)	(3.732)	(4.922)	(5.864)
2012	0.375***	0.362***	0.170***	0.162***
	(4.193)	(4.250)	(3.886)	(5.757)
2013	0.304***	0.301***	0.218***	0.196***
	(4.149)	(4.327)	(4.578)	(5.958)
2014	0.295***	0.289***	0.199***	0.213***
	(3.742)	(3.874)	(4.088)	(5.909)
CONSTANT	0.187	0.071	-0.296	-0.708*
	(0.687)	(0.573)	(0.527)	(0.424)
OBSERVATIONS	23,175	23,175	49,369	49,369
NUMBER OF CSO_REF	5,835	5,835	10,812	10,812
AR(1) Z-STATISTIC	-1.440	-1.685	-2.749	-1.858
AR(1) Z-STATISTIC P-VALUE	0.150	0.0919	0.00598	0.0632

AR(2) Z-STATISTIC	-0.182	-0.161	0.491	-1.263
AR(2) Z-STATISTIC P-VALUE	0.855	0.872	0.623	0.207
HANSEN TEST	19.62	18.09	17.37	4.847
HANSEN TEST P-VALUE	0.418	0.581	0.136	0.564
STANDARD ERRORS IN PARENTHESES *** P<0.01, ** P<0.05, * P<0.1				

Table A.4 -3 The foreign ownership effect in the South East and North of England

A.4.4 The effect of foreign ownership in the North East over time

VARIABLES	
INTERMEDIATE INPUTS	0.742***
	6.504
EMPLOYMENT	0.568***
	3.434
CAPITAL	0.570**
	2.445
AGE	-0.117
	-1.527
MULTI SIC	-0.0236
	-0.775
MULTI REGION	0.0410
	1.204
SINGLE	-0.0815*
	-1.851
HERFINDAHL	0.189*
	1.677
INTERACTIONS	**FO**
1986	0.0821
	(1.590)
1987	0.0883
	(1.554)
1988	0.0388
	(0.931)
1989	0.0426
	(1.076)
1990	0.0157
	(0.419)
1991	-0.0537
	(-1.255)
1992	-0.0304
	(-0.782)
1993	-0.0247
	(-0.547)
1994	0.0165
	(0.349)
1995	0.0583
	(1.274)
1996	0.0740
	(1.138)

1997	0.0106
	(0.0758)
1998	0.0287
	(0.392)
1999	-0.0895
	(-1.313)
2000	-0.0231
	(-0.338)
2001	-0.0661
	(-1.130)
2002	-0.00204
	(-0.0303)
2003	-0.0194
	(-0.307)
2004	-0.00210
	(-0.0171)
2005	-0.0795
	(-1.021)
2006	0.0709
	(1.307)
2007	0.161***
	(2.950)
2008	0.0805
	(1.641)
2009	0.207***
	(2.912)
2010	0.164***
	(2.973)
2011	0.0442
	(0.873)
2012	-0.0116
	(-0.0999)
2013	0.0335
	(0.239)
2014	0.104
	(1.160)
SIC 23	-0.187
	(-1.531)
SIC 24	0.235
	(3.037)
SIC 25	0.105*
	(1.816)
SIC 26	0.257*
	(1.859)
SIC 31	0.279**

	(2.341)
SIC 32	0.334***
	(2.741)
SIC 33	0.250
	(1.565)
SIC 34	0.0824
	(0.920)
SIC 35	0.163
	(1.603)
SIC 36	0.304*
	(1.773)
SIC 37	0.360**
	(2.323)
SIC 41	0.0970
	(0.717)
SIC 42	0.198***
	(3.064)
SIC 43	0.202
	(1.351)
SIC 44	0.246
	(1.530)
SIC 45	0.187
	(1.135)
SIC 46	0.174
	(1.383)
SIC 47	0.258**
	(2.492)
SIC 48	0.104
	(1.290)
SIC 49	0.247**
	(2.133)
1986	-0.022
	0.035
1987	-0.005
	0.059
1988	0.001
	0.048
1989	0.049
	0.061
1990	0.033
	0.06
1991	-0.15
	0.061
1992	-0.052
	0.078

1993	0.084
	0.099
1994	0.112
	0.0109
1995	0.117
	0.095
1996	0.21
	0.117
1997	-0.152
	0.113
1998	0.062
	0.101
1999	-0.207
	0.079
2000	0.052
	0.118
2001	-0.031
	0.083
2002	0.072
	0.158
2003	0.007
	0.117
2004	-0.226
	0.169
2005	0.107
	0.136
2006	0.18
	0.01
2007	0.288
	0.214
2008	0.339
	0.167
2009	0.076
	0.147
2010	0.481
	0.176
2011	0.233
	0.122
2012	0.399
	0.169
2013	0.404
	0.147
2014	0.207
	0.1

CONSTANT	-0.244
	(0.317)
OBSERVATIONS	9,390
NUMBER OF CSO_REF	2,117
AR(1) Z-STATISTIC	-3.643
AR(1) Z-STATISTIC P-VALUE	0.000269
AR(2) Z-STATISTIC	-0.181
AR(2) Z-STATISTIC P-VALUE	0.856
HANSEN TEST	51.76
HANSEN TEST P-VALUE	0.000538
STANDARD ERRORS IN PARENTHESES *** P<0.01, ** P<0.05, * P<0.1	

Table A. 4-4 The effect of foreign ownership in the North East over time

A.4.5 The effect of Foreign ownership in the North East of England over time

VARIABLES			
INTERMEDIATE INPUTS	0.668		
	(15.10)		
EMPLOYMENT	0.333		
	(7.404)		
CAPITAL	0.0179		
	(0.617)		
AGE	-0.0331		
	(-0.796)		
MULTI SIC	0.0214		
	(1.542)		
MULTI REGION	0.0384		
	(1.616)		
SINGLE	0.00522		
	(0.241)		
HERFINDAHL	0.0650		
	(0.898)		
INTERACTION DUMMIES	**EU**	**ROW**	**US**
1986	0.0717	0.183***	0.0342
	(0.396)	(3.611)	(0.506)
1987	0.0758	*	0.0534
	(0.954)		(0.863)
1988	-0.0570	0.118*	0.0399
	(-1.023)	(1.943)	(1.011)
1989	-0.0518	0.0566	0.0675*
	(-0.960)	(0.846)	(1.921)
1990	-0.0383	0.0198	0.0265
	(-0.625)	(0.289)	(0.718)
1991	0.0153	0.0773	0.0562
	(0.278)	(0.910)	(1.509)
1992	-0.0127	0.0141	0.0912**
	(-0.186)	(0.324)	(2.086)
1993	-0.0144	-0.0519	0.0853*
	(-0.230)	(-1.600)	(1.948)
1994	0.00513	-0.0193	0.0749*
	(0.124)	(-0.432)	(1.731)
1995	0.00681	0.0570**	0.166***
	(0.166)	(1.995)	(3.930)
1996	-0.0384	0.0471	0.112*
	(-0.738)	(0.580)	(1.956)
1997	0.200**	0.0928*	0.0945
	(2.467)	(1.929)	(0.932)

1998	0.0523	-0.0321	0.219**
	(1.081)	(-0.549)	(2.034)
1999	0.0150	0.0392	0.186***
	(0.391)	(0.905)	(2.821)
2000	0.0765	0.0188	0.0896*
	(1.433)	(0.356)	(1.847)
2001	0.0409	0.0162	0.0916**
	(1.045)	(0.265)	(2.083)
2002	0.0138	0.0196	0.124**
	(0.313)	(0.433)	(2.554)
2003	-0.00444	0.0203	0.185***
	(-0.121)	(0.478)	(3.256)
2004	-0.0625	-0.177	0.127
	(-0.799)	(-1.382)	(1.321)
2005	-0.0883*	-0.0985	-0.0127
	(-1.890)	(-1.292)	(-0.280)
2006	0.00120	-0.000859	-0.0144
	(0.0351)	(-0.0126)	(-0.363)
2007	0.0557	0.0632	0.0408
	(1.333)	(1.291)	(0.443)
2008	-0.00312	-0.0227	0.134**
	(-0.0642)	(-0.279)	(2.291)
2009	-0.0893	-0.0436	0.121
	(-1.154)	(-0.555)	(1.129)
2010	-0.0865	-0.0817	0.0384
	(-1.582)	(-1.380)	(0.605)
2011	-0.0584	-0.101	0.0823
	(-0.877)	(-1.464)	(1.620)
2012	0.250**	0.0206	0.196***
	(2.454)	(0.439)	(2.875)
2013	0.344***	-0.00547	0.134
	(2.926)	(-0.113)	(1.427)
2014	0.0968*	0.0541	0.131
	(1.704)	(0.910)	(1.235)
SIC 23	-0.213***		
	(-2.615)		
SIC 24	0.0692		
	(1.558)		
SIC 25	0.0801*		
	(1.947)		
SIC 26	0.0672		
	(1.061)		
SIC 31	0.00788		
	(0.157)		
SIC 32	0.0492		

	(1.049)
SIC 33	-0.0740
	(-1.333)
SIC 34	-0.0633
	(-1.478)
SIC 35	-0.0224
	(-0.468)
SIC 36	-0.0950
	(-1.214)
SIC 37	0.0279
	(0.424)
SIC 41	-0.181***
	(-3.224)
SIC 42	0.0804*
	(1.738)
SIC 43	-0.108*
	(-1.716)
SIC 44	-0.0589
	(-0.516)
SIC 45	-0.140**
	(-2.130)
SIC 46	-0.146***
	(-3.127)
SIC 47	0.0554
	(1.190)
SIC 48	-0.0461
	(-1.197)
SIC 49	0.0485
	(0.750)
1986	-0.021
	0.015
1987	-0.025
	0.015
1988	-0.028
	0.021
1989	-0.049
	0.02
1990	-0.052
	0.021
1991	-0.118
	0.024
1992	-0.123
	0.025
1993	-0.052
	0.027

1994	-0.014
	0.029
1995	-0.047
	0.026
1996	0.039
	0.03
1997	-0.162
	0.04
1998	-0.113
	0.03
1999	-0.171
	0.03
2000	-0.124
	0.03
2001	-0.154
	0.034
2002	-0.144
	0.038
2003	-0.178
	0.037
2004	-0.082
	0.036
2005	-0.088
	0.036
2006	-0.063
	0.038
2007	-0.062
	0.046
2008	-0.068
	0.05
2009	-0.053
	0.064
2010	0.02
	0.05
2011	0.032
	0.039
2012	0.073
	0.043
2013	0.099
	0.044
2014	0.008
	0.043
CONSTANT	-0.429*
	(0.221)

OBSERVATIONS	9,390
NUMBER OF CSO_REF	2,117
AR(1) Z-STATISTIC	-3.264
AR(1) Z-STATISTIC P-VALUE	0.00110
AR(2) Z-STATISTIC	-1.080
AR(2) Z-STATISTIC P-VALUE	0.280
HANSEN TEST	52.07
HANSEN TEST P-VALUE	0.189
STANDARD ERRORS IN PARENTHESES *** P<0.01, ** P<0.05, * P<0.1	

Table A.4 -5 The effect of Foreign ownership in the North East of England over time

A.5 Cluster estimation methods

A.5.1 Ward's Hierarchical grouping

Another cluster function that is widely used to define clusters is Ward's hierarchical grouping (1963), a widely used method to establish groupings and subsets based on a number of variables. Unlike previous methods (Ward highlights Cox, 1957, and Fisher, 1958, as examples), Ward's method of grouping uses a number of variables to form groups, or clusters, unlike Cox and Fisher where only a single variable is used to form the groupings. Ward also states when creating groupings, some information will be lost. To minimise this, Ward forms groupings individually systematically until all desired grouping are formed and there is a set of mutually exclusive subsets. These then evaluate the loss of information in terms of criterion used to establish the groupings. Ward's method is commonly used to create clusters of industries or countries. Batog (2017) created clusters of EU countries to analyse the dynamics and differences in labour productivity over a twenty year time period, 1994-2014. Using Ward's method to create clusters allowed him to create groups of countries based upon labour compensation, labour productivity and annual worked hours per worker, which resulted in two labour force profiles being created: High GDP per capita and Low GDP per capita. Batog does highlight that the Ward's method of grouping fails to deal with outliers within the data. Krontahaler (2005) used the Ward's clustering method to form groups of homogenous groups, or clusters, of Germans regions to compare the economic capability of said clusters based in West German regions with those in East German regions.

A.5.2 Centroid-based density functions

Another option are the centroid-based density functions, examples being Kmeans and Kmediums. These centroid-based density functions are techniques that use the mean or medium to sort instances into groups, so called K. These groups, or clusters, are defined through two steps (Davidson, 2002):

1) Assigning instances into groups with similar values
2) These groups are re-estimated to allocate these instances into better fitting groups.

Step two occurs until convergence occurs, or the sum of square error is the smallest. An example of the allocation of instances into groups is when there are two groups A and B and an instance with the probabilities of *a* and *b*. If *a* greater than *b* then the instance would be allocated to group A (Davidson, 2002). This allocation will occur until all instances are allocated into groups using the Nearest-Neighbour rule (Zhang et al., 2008). The number of groups, K, is user defined, which in itself is a limitation of the process, too many or two few groups which would have a detrimental impact upon the groups.

A.5.3 Delgado's Clustering Algorithm

Delgado et al (2016) developed a clustering algorithm that assesses industries and organises them into clusters based upon a mixture of meso-level and micro-level methods using US industry data, using the 2007 North American Industry Classification System (NAICS) for the 2009 Country Business Patterns (CBP) across this whole economy (minus farming and Government activities). They chose to use traded industries (which are industries that are geographically concentrated) which resulted in 778 traded industries being used to develop the clusters. They use 6-digit NAICS industry codes to create a cluster configuration containing 51 clusters, using inter-industry linkages based upon co-locations patterns, input-output links, and labour occupation similarities.

The clustering algorithm assess these inter-industry linkages and organises the different industries into clusters with other industries that have similar linkages to develop sets of cluster configurations.

The algorithm has the ability to generate a number of different cluster configurations, labelled as *C,* which are made up of individual clusters *c*. These configurations and clusters are individually scored and evaluated to establish the configuration that captures most inter-industry linkages. Delgado et al (2016) present a five-step process to establish the cluster configurations. Firstly, they used cluster definitions (comparable and region-specific) to define a similarity matrix (M_{ij}) that captures the relatedness between two industries. This is followed by establishing broad parameter choices (β) that are defined by the user. Once these are in place, the clustering function, C=F(M_{ij}, β), can be calculate to create a configuration *C*. This will produce a number of cluster configurations. Therefore, performance scores are calculated for each C to identify cluster configuration, *C**, with most inter-industry linkages. Finally, the finalised configuration *C***, or Benchmark Cluster Definitions (BCD), is developed by assessing and correcting the individual clusters in *C*.*

Similarity Matrices

The similarity matrices ($M_{ij,}$) are based upon the user's choice of indicator[60] and the similarity measures[61] . They are used to establish relatedness between two industries *i* and *j.*

Cluster definitions

The inter-industry linkages are defined using different types of clusters which can be separated into two different definitions. These are: Comparable cluster definitions[62] or Region-Specific cluster definitions[63].

Comparable Cluster Definitions

Comparable clusters allocate a fixed set of individual industries into specific clusters, allowing for direct comparison across the same clusters in different regions. Delgado et al (2016) highlight three existing comparable cluster definitions:

- *Knowledge Clusters*

  Knowledge clusters are formed when there are groups of industries that use similar technological bases and share a common science. Those plants that share similar traits are more likely to share inputs and workforce, and therefore more likely to co-locate together to benefit from these shared traits.

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[60] These could be employment, number of establishments, buyer-supplier linkages, and shared labour requirements.

[61] The similarity measure is how the distance between two industries is measured, such as correlation coefficient, Euclidean, Jaccard index or user defined.

[62] clusters based upon inter-industry from multi-region analysis.

[63] observed linkages among industries or firms within a single region.

- *Input-Output (IO) clusters*

  Input-output linkages between industries is another way to define clusters. This data can show the relationship within and between industries, so it is possible to establish how important one industry is to another industry.

- *Co-Location-based Clusters*

  The final comparable cluster definition is that of co-location-based clusters. By taking into account the location of industries it is possible to capture agglomeration spillovers that may occur between plants.

Region Specific Cluster Definitions

The region-specific clusters can be used to enhance the information captured by the comparable cluster definitions. While comparable clusters can capture economic activity and are required for cluster analysis across regions, they are unable to highlight specific inter industry linkages that occur within specific regions. They are unable to identify “driver” industries within regions. To overcome these limitations, region specific clusters are included to capture this information. However, to solely use these types of cluster definitions could result in activities that are not present in that region, even though related to industries within the region being examined, being excluded.

Types of similarity matrices

Delgado et al (2016) defined similarity matrices into three types: Co-location, National-Level, and multidimensional. The similarity matrices use cluster definitions in combination to calculate cluster configurations.

Co-Location

The first type of similarity matrices is based upon co-location patterns across a variety of regions to establish the inter-industry linkages. Based upon Porter (Porter, 2003), these similarity matrix definitions are based upon location correlation (LC) between plants within regions. Porter (2003) developed employment co-location, defined “as the correlation coefficient between employment in industry *i* and employment in industry *j* in a region *r.”*

$$LC - Employment_{i,j} = Correlation\left(Employment_{ir}, Employment_{jr}\right)$$

Equation A8-1 LC-Employment

Delagdo et al (2016) introduce an additional LC correlation based up the count of establishments within a region for industry *i* and industry *j*, called LC-establishments.

$$LC - Establishments_{i,j} = Correlation\left(Establishments_{ir}, Establishments_{jr}\right)$$

Equation A8-2 LC-Establishments

This inclusion of the co-location pattern of the count of establishments within a region can help capture any spillovers that could occur due to the number of establishments present, as Glaeser and Kerr (2009) suggested. These LC matrices are useful in establishing any inter-industry linkages; however, they are sensitive to the size of the region and can resulting being biased, especially if the region is relatively large in size.

The final co-location matrix, called the co-agglomeration index (COI), was developed by Ellison and Glaeser (1997)[64] and is used to establish whether two industries are more co-located than expected if their employment was normally distributed.

$$COI_{ij} = \sum_{r} (s_{ri} - x_r)(s_{rj} - x_r) / \left(1 - \sum_{r} x_r^2\right)$$

Equation A8-3 Co-agglomeration index (COI)

The higher the positive value of the COI, the greater the likelihood for externalities between the two industries to occur. However, the size of the effect is difficult to establish.

National Level

The second type of similarity matrices are based at the national level. The national-level inter-industry links are not geographically bounded as they do not consider location patterns. This makes it possible for them to capture industry interdependencies that are not limited to location. The two matrices considered and that use national data are the Input-output (IO) and Labour Occupation links (OCCs).

The IO links is based upon the Benchmark IO Accounts of the United States[65] and captures the supplier and buyer flows between industries.

$$IO_{ij} = Max\{input_{i\to j}, input_{i\leftarrow j}, output_{i\to j}, output_{i\leftarrow j}\}$$

Equation A8-4 Input Output (IO) links

They construct a symmetric IO link between pairs of industries *i,j* based upon the maximum unidirectional input and output links. It examines the share of inputs and outputs of industry *i* that come from industry *j* on a scale of 0 (do not buy from one another) to 1 (solely buy from one another).

The OCC matrix looks at labour occupation links and is used to measure the extent to which industry share similar skills. They construct a pairwise correlation between occupation composition between industry *i* and industry *j.*

$$Occ_{ij} = Correlation(Occupation_i, Occupation_j)$$

Equation A8-5 Labour occupation links

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[64] Delagdo et al (2016) have used the revised version of the COI index, presented by Ellison et al (2010)

[65] These are benchmark tables that show statistical description of the production of goods and services with transaction flows of goods and services between different industries and to different components of final uses. The data is compiled very five years, in line with the economic census years in the U.S. Since 2007, they have become fully integrated with annual industry accounts, national income, and product accounts.

Delgado et al (2016) use the 2009 data of the OES Survey of the Bureau of Labor Statistics[66] which provides 792 non-governmental occupations and information on the prevalence of these occupation for each industry.

Multidimensional similarity matrices

The third similarity matrices are a combination of the co-location and national level matrices. These are created by averaging the unidimensional matrices from the co-location and national level to create combinations of matrices. The use of these multidimensional matrices can overcome some of the limitations the individual matrices pose, and the combination of these matrices reduces the level of noise by averaging across multiple matrices.

Parameter Choices

Once the matrices for the similarity matrix are established, the parameter choices, labelled as β, are now inputted. These parameter choices include the initial number of clusters, how the underlying data should be normalised, and the determination of the starting values for the clustering function. These inputs are defined by the user and will depend upon what data is being used.

The number of clusters calculated, labelled as *numc*, are defined by the user. It is paramount that the correct number of clusters is identified, as having too fewer or too many clusters would result in weak cluster definitions. There is currently no conclusive method of identifying the optimal number of clusters (Everitt et al., 2011). In other cluster definitions, Porter (2003) established 41 clusters and Feser (2005) established 45 IO based clusters. Using these as a guide and regarding their data[67], Delgado et al (2016) initially decided to set the number of clusters to be calculated between 30 and 60 clusters per similarity matrix.

The remaining parameters refer to the data: the starting values and type of normalisation for the clustering functions. The starting values for the algorithm are chosen at random. The treatment of the underlying data can either be left untransformed (raw), or it can be row standardised. However, this is only required when the clustering functions are *kmeans* or *kmediums* as it can result in a better centroid for each individual cluster. Delgado et al (2016) highlighted that this process also had a limitation in relation to the data being used in her algorithm. The data across all datasets need to be directly compatible, which could result in some data being exclude from the analysis. To overcome this, a hierarchal approach would be more appropriate as it does not require directly compatible datasets.

Once the user has defined these broad parameters and included the various similarity matrices, the clustering function can now be used to generate different configurations (C).

[66] The OES, or Occupational Employment Statistics program, is a semi-annual survey, every six months, in the U.S. that is designed to produce estimates for wages and employment for specific occupations, 792 occupations in total.

[67] Delgado et al (2015) have 778 industries across 66 different three digit NAICS codes

Clustering Function

The clustering function (C= $F(M_{ij,}\beta)$) combines the similarity matrices and parameter choices to compute the cluster configurations. The aim of the function is to find the greatest relatedness among industries within clusters.

The function can be run a number of times with various combinations of similarity matrices and user defined parameters. This can result in a large number of possible configurations, so a mechanism is required to enable the user to establish which of these *Cs* is the best representative of industry clusters. Unlike previous techniques, this algorithm produces scores for each configuration to analyse which configuration is the best representation of clusters. A "good" set of clusters is when the industries within a cluster are closely related with each other more than other industries in separate clusters. They developed a score approach to assess this by using alternative measures of inter-industry linkages. This would produce a validation score (VS) for each configuration based on alternative industry measures.

Performance Scores

This is done by calculating validation scores (VS) for each cluster configuration and for each industry within the clusters. The VS-Cluster scores examine the fit of individual cluster within the configuration to establish whether they are meaningfully different from other clusters in the same configuration. The VS-Industry scores examine the fit of each industry within its cluster. The aim of this is find a cluster configuration where the industries and clusters have a high Within Cluster Relatedness (WCR) in relation to Between Cluster Relatedness (BCR) with other clusters in the configuration.

These scores are calculated with using four distinct matrices: LC-Emp, LC-Est, IO and Occ. These matrices are not dependent upon the similarity matrix used to calculate C*. Sub-scores can be calculated and compared consistently no matter that the similarity matrix used to calculate *C.*

There are WCR scores calculated for each cluster, defined as the average relatedness between pairs of industries with a cluster (WCR_c), and for each individual industry, defined as the relatedness of industries to other industries within the same cluster (WCR_{ic}). The between cluster relatedness scores for the clusters is the average relatedness between industries in a cluster compared to industries in another cluster (BCR_c). Each cluster within the configuration has a BCR scored calculated between it and every other cluster. Then to establish the threshold to compare to compare the WCR scores to, the average and the 95th percentile values are calculated. This is done by calculating the percentage of clusters that have a WCR_c score that is greater than the BCR_c. Firstly, the percentage of clusters have a higher WCR_c than the Average BCR_c for that particular cluster configuration, M_{ij}, to create the VS-Cluster Avg sub-score. Then the WCR_c score is compared to the more restrictive 95th Percentile BCR_c value to calculate the VS-Cluster Pctile95 subscore.

The equations below present the formula for calculating these scores:

$$VS - Cluster\ Avg_C^M = \left(100/_{N_c}\right) * \sum_c I\left[WCR_c(M_{ij}) > AvgBCR_c(M_{ij})\right]$$

Equation A8-6 Validation score for Clusters Average

$$VS - Cluster\ Pctile95_C^M = \left({}^{100}/_{N_c}\right) * \sum_c I\left[WCR_c(M_{ij}) > Pctile95BCR_c(M_{ij})\right]$$

Equation A8-7 Validation score for Clusters 95th percentile

These scores are then averaged to get the VS-Cluster score which is used to calculate the final VS score of the cluster configuration.

The other part of the VS score comes from the individual industries from within the clusters, VS-Industry. This score examines the fit of the individual industries within the clusters in comparison to industries outside of the cluster. This differs from the VS-Cluster score as it was comparing the average of the industry scores within the cluster with the average of the industries scores from another cluster. This is examining how the industries in a score are related compared to industries outside that cluster. Like with the VS-cluster calculation, each industry gets a WCR_{ic} score and this is compared with the average BCR_i (VS-Industry Avg) and the 95th percentile BCR_i (VS-Industry Pctile95). The average of these sub-scores then provides the VS-Industry score, the other half of the VS score for the cluster configuration.

Now that both the VS-Cluster and VS-industry scores have been calculated, these are averaged to get the final VS score for the cluster configuration. This VS score is then used to rank each cluster configuration to find the one which has the most meaningful clusters.

Finalised Configuration

Once the C* configuration has been established, the individual clusters need to be examined to establish whether the industries within them are a good fit. Due to limitations in the underlying data, some industries may be better placed into different clusters. This can be done either by identifying any outliers that would sit better in a different cluster or whether some clusters should be better off combined or split up. They define two types of outliers that could be present: systematic and marginal.

Systematic outliers are industries that have an overall low WCR score based upon the average of the four matrices. These are identified when the industry WCR is low relative to other industries within the cluster (is two standard deviations below average WCR) or when the WCR is low relative to industries in other clusters (below the 75th percentile). Once they have been identified, these industries can be reassigned to a cluster where the WCR is highest. This process is done using the algorithm and is repeated until there are no systematic outliers remaining.

Marginal outliers are industries that may have high WCR but would be better off in a different cluster. Delgado et al (2016) state that this type of cluster analysis is not a perfect substitute for expert judgement and that there can be instances where there needs to correction of anomalies and characterisation of individual sectors. These industries are reassigned by comparing the industry definitions with the overall cluster definition based upon the definitions from the industry codes. These outliers can then be reallocated to the 'next best' cluster based upon the WCR scores. This is not done using an algorithm but done using judgement based upon the definitions and WCR scores. It is important to ensure than any movements between clusters are tracked and recorded to ensure transparency.

The size of clusters also needs to be assessed in case there are clusters who either share a high BCR and have similar industry classification definitions, or vice versa. It is suggested that these clusters with the high BCR are combined, or if they have a low BCR, separated into different clusters. These changes are not made using the algorithm, so any changes to the clusters need to be documented clearly and accurately so there is transparency.

Once all of these steps have been completed, then the finalised set of clusters, called C** or Benchmark Cluster Definitions (BCD), can be presented. The BCD can now be used in any estimations or analysis. They are not bound by location or are region specific and allows for comparisons between regions.

Delgado Cluster configuration for US NAICS classification

Cluster Code	Cluster Name	No. of Industries	WCR_c
1	Aerospace Vehicles and Defence	7	2.21
2	Agricultural Inputs and Services	9	0.83
3	Apparel	21	2.28
4	Automotive	26	2.26
5	Biopharmaceuticals	4	3.33
6	Business Services	33	1.18
7	Coal Mining	4	2.28
8	Communications Equipment and Services	8	2.36
9	Construction Products and Services	20	1.79
10	Distribution and Electronic Commerce	62	2.18
11	Downstream Chemical Products	13	1.29
12	Downstream Metal Products	16	1.02
13	Education and Knowledge Creation	15	1.33
14	Electric Power Generation and Transmission	5	0.90
15	Environmental Services	7	2.80
16	Financial Services	26	2.03
17	Fishing and Fishing Products	5	3.38
18	Food Processing and Manufacturing	47	0.81
19	Footwear	6	5.17
20	Forestry	4	3.52
21	Furniture	12	1.37

22	Hospitality and Tourism	31	0.44
23	Information Technology and Analytical Instruments	27	1.30
24	Insurance Services	8	4.32
25	Jewellery and Precious Metals	4	5.46
26	Leather and Related Products	6	1.32
27	Lighting and Electrical Equipment	15	1.49
28	Livestock Processing	5	1.18
29	Marketing, Design, and Publishing	22	1.68
30	Medical Devices	5	2.12
31	Metal Mining	8	0.62
32	Metalworking Technology	17	1.48
33	Music and Sound Recording	5	6.16
34	Nonmetal Mining	13	0.73
35	Oil and Gas Production and Transportation	12	1.47
36	Paper and Packaging	20	1.62
37	Performing Arts	8	1.64
38	Plastics	15	2.03
39	Printing Services	13	2.53
40	Production Technology and Heavy Machinery	41	1.08
41	Recreational and Small Electric Goods	15	1.30
42	Textile Manufacturing	23	1.19
43	Tobacco	3	7.47
44	Trailers, Motor Homes, and Appliances	9	0.52
45	Transportation and Logistics	17	1.13
46	Upstream Chemical Products	12	1.23
47	Upstream Metal Manufacturing	26	0.99
48	Video Production and Distribution	6	3.37
49	Vulcanized and Fired Materials	17	0.90

50	Water Transportation	12	1.71
51	Wood Products	13	1.70

Table A.5 -6 Delgado Cluster configuration for US NAICS classification

A.6 Validation Scores

A.6.1 Complete Validation Scores for the top ten cluster configurations

CLUSTER CONFIG	NUMBER	MAX IND	VS CLUSTER AVG	VS INDUSTRY AVG	VS CLUSTER 95%	VS INDUSTRY 95%	VS CLUSTER AVG PC	VS INDUSTRY AVG PC 95%	VS	RANK VS CLUSTER AVG PC 95%	RANK VS INDUSTRY AVG PC 95%	RANK VS
IO LC 46	46	11	98.37	99.14	86.96	69.57	92.66	84.36	88.51	1	1	1
IO LC 49	49	9	98.47	98.86	86.74	69.00	92.60	83.93	88.27	2	4	2
IO LC 47	47	11	97.87	99.00	86.70	69.29	92.29	84.14	88.22	3	3	3
IO LC 48	48	10	97.92	98.86	85.42	69.57	91.67	84.21	87.94	9	2	4
IO LC 45	45	11	98.33	99.00	85.56	68.57	91.94	83.79	87.87	7	5	5
IO LC 44	44	11	97.73	98.43	85.80	69.00	91.76	83.71	87.74	8	6	6
IO LC -EMP 50	50	11	99.00	98.14	85.50	68.14	92.25	83.14	87.70	4	12	7
IO LC 50	50	9	97.00	98.43	87.00	68.14	92.00	83.29	87.64	6	10	8
IO LC 42	42	11	98.21	98.71	84.52	68.71	91.37	83.71	87.54	11	6	9
IO LC -EMP 49	49	11	98.98	98.14	85.20	67.57	92.09	82.86	87.47	5	19	10

Table A6-1 Complete Validation Scores for the top ten cluster configurations

A.6.2 Underlying VS score of the evaluation matrix

CLUSTER CONFIG	VS CLUSTER LCEST	VS INDUSTRY LCEST	VS LCEST	VS CLUSTER LCEMP	VS INDUSTRY LCEMP	VS LCEMP	VS CLUSTER IO	VS INDUSTRY IO	VS IO	VS CLUSTER OCC	VS INDUSTRY OCC	VS CLUSTER OCC
IO LC 46	93.48	80.00	86.74	89.13	74.29	81.71	89.13	95.71	92.42	98.91	87.43	93.17
IO LC 49	94.90	79.71	87.31	90.82	74.29	82.55	85.71	94.57	90.14	98.98	87.14	93.06
IO LC 47	93.62	78.86	86.24	89.36	73.71	81.54	87.23	95.71	91.47	98.94	88.29	93.61
IO LC 48	93.75	79.43	86.59	89.58	74.29	81.94	84.38	94.57	89.47	98.96	88.57	93.77
IO LC 45	92.22	79.14	85.68	87.78	73.43	80.60	88.89	95.71	92.30	98.89	86.86	92.87
IO LC 44	92.05	78.57	85.31	87.50	72.57	80.04	88.64	95.43	92.03	98.86	88.29	93.58
IO LC -EMP 50	90.00	73.43	81.71	89.00	73.14	81.07	90.00	97.14	93.57	100.00	88.86	94.43
IO LC 50	95.00	78.86	86.93	91.00	73.43	82.21	82.00	93.71	87.86	100.00	87.14	93.57
IO LC 42	90.48	77.71	84.10	86.91	72.00	79.45	90.48	96.29	93.38	97.62	88.86	93.24
IO LC -EMP 49	89.80	73.14	81.47	88.78	72.57	80.67	89.80	97.14	93.47	100.00	88.57	94.29

Table A6-2 Underlying VS score of the evaluation matrix

A.7 Original Cluster Configuration

A.7.1 Cluster names with plant count and total employment

Cluster	Cluster name	WCRc	Number of plants	Total Employment
1	**Ferrous metals and manufacturing**	2.227	**47,337**	**2,730,136**
2	**Non-ferrous metal Manufacturing**	2.083	144,130	3,432,349
3	**Metal Manufacturing**	1.951	604,429	11,816,831
4	**Mineral Extraction**	1.817	24,751	882,671
5	**Other Minerals extraction**	2.284	2,759	53,638
6	**Mineral Manufacturing**	2.014	135,839	2,564,540
7	**Building Materials**	2.159	74,605	1,270,949
8	**Miscellaneous Manufacturing**	0.845	286,521	6,752,143
9	**Bread and Biscuits**	2.851	124,819	3,765,286
10	**Large transport Manufacturing**	1.355	78,881	5,226,903
11	**Soaps and Perfumes**	2.517	17,863	942,793
12	**Grain and Starch**	2.09	4,995	207,010
13	**Pet feeds**	2.599	21,219	517,638
14	**Leather working**	2.199	27,284	359,714
15	**Paints**	2.368	20,353	708,192
16	**Processing of food stuffs**	2.262	24,743	1,234,801
17	**Explosives and ordance**	1.963	6,032	583,749
18	**Cooking fats and oils**	1.925	2,254	121,515
19	**Processing meats**	2.463	37,412	2,736,954
20	**Sugar**	2.284	579	109,309
21	**Confectionary**	2.714	57,135	2,877,066
22	**Paper Products**	2.191	78,362	2,483,328
23	**Printing products**	2.388	771,320	9,434,424
24	**Distilling and compounding**	2.284	6,575	348,332
25	**Brewing and Tobacco**	1.807	19,670	1,091,137

26	**Recreational Manufacturing**	2.228	318,502	2,319,685
27	**Precision Apparatus**	2.187	95,291	1,978,970
28	**Inorganic and organic chemicals**	1.805	22,231	1,527,666
29	**Essential oils**	2.284	2,121	86,875
30	**Chemical and Adhesives**	2.07	36,932	1,158,463
31	**Man Made Fibre Production**	2.284	1,012	152,368
32	**Rubber tyres**	2.284	2,282	421,318
33	**Plastic and rubber products**	2.574	207,927	5,771,510
34	**Electronic Equipment**	2.054	231,853	6,285,035
35	**Wood manufacturing**	2.071	301,682	3,829,048
36	**Wall Coverings**	2.284	1,484	109,333
37	**Synthetic rubber**	2.284	532	37,758
38	**Tractors**	2.284	1,368	171,019
39	**Vehicles**	1.906	126,912	6,863,115
40	**Textiles**	2.256	84,866	2,420,896
41	**Other Textiles**	1.942	67,277	685,908
42	**Clothing**	2.137	230,662	5,015,377
43	**Metal and Chemical Machinery**	2.43	421,863	6,442,840
44	**Commercial Machinery**	1.671	70,211	2,281,542
45	**Mining machinery**	2.284	4,756	247,552
46	**Other manufacturing**	2.161	282,086	7,045,327

Table A.7.1 Cluster names with plant count and total employment

A.7.2 Cluster configuration with Industry names and plant count

Cluster	Industry Code	Industry Name	WCRi	WCRc	Number of plants	Total Employment
		Ferrous metals and manufacturing			**47,337**	**2,730,136**
1	2210	Iron and Steel Industry	0.805	2.227	6,028	1152141
1	2220	Steel Tubes	1.041	2.227	8,568	415496
1	2234	Drawing and manufacture of steel wire and steel wire products	1.042	2.227	13,643	382177
1	2235	Other drawing, cold rolling, and cold forming	0.934	2.227	4,486	117459
1	3111	Ferrous metal foundries	1.023	2.227	14,612	662863
		Non-ferrous metal Manufacturing			**144,130**	**3,432,349**
2	2245	Aluminium and aluminium alloys	1.012	2.083	8,350	370047
2	2246	Copper, brass and other copper alloys	0.863	2.083	4,789	221895
2	2247	Other Non-ferrous metals and their alloys	0.857	2.083	8,470	280083
2	3112	Non-ferrous metal foundries	1.081	2.083	11,607	391827
2	3120	Forging, pressing and stamping	1.108	2.083	44,673	993151
2	3137	Bolts, nuts etc; Springs; Non Precision chains	1.018	2.083	20,685	484896
2	3138	Heat and surface Metal treatment, including sintering	1.111	2.083	45,556	690450
		Metal Manufacturing			**604,429**	**11,816,831**
3	3142	Metal Doors, Windows etc	0.947	1.951	35,142	525066
3	3162	Cutlery, spoons, forks and similar table ware, razors	0.318	1.951	2,230	75257
3	3164	Packaging products of metal	0.683	1.951	9,055	465532
3	3165	Domestic heating and cooking appliances (non electrical)	0.465	1.951	4,562	214811
3	3204	Fabricated constructional steelwork	0.956	1.951	63,683	1393796
3	3205	Boilers and process plant fabrications	0.881	1.951	36,801	797515
3	3261	Precision chains and other mechanical power transmission equipment	0.911	1.951	44,785	585878
3	3287	Pumps	0.856	1.951	12,667	428039
3	3288	Industrial valves	0.783	1.951	8,326	429356
3	3289	Mechanical, marine and precision engineering NES	0.995	1.951	358,821	3146933

3	3640	Aerospace equipment manufacturing and repairing	0.554	1.951	28,357	3754648
		Mineral Extraction			**24,751**	**882,671**
4	2330	Salt Extraction and Refining	0.703	1.817	263	15024
4	2489	Ceramic goods	0.703	1.817	24,488	867647
		Other Minerals extraction			**2,759**	**53,638**
5	2396	Extraction of other minerals	1.523	2.284	2,759	53638
		Mineral Manufacturing			**135,839**	**2,564,540**
6	2410	Structural Clay Products	0.827	2.014	9,446	348336
6	2450	Working of Stone and other Non Metallic minerals	0.896	2.014	74,034	882447
6	2460	Abrasive Products	0.858	2.014	7,735	128831
6	2471	Flat glass	0.942	2.014	18,545	479806
6	2478	glass containers	0.627	2.014	3,007	208356
6	2479	other glass products	0.805	2.014	17,284	329938
6	2481	Refractory good	0.794	2.014	5,788	186826
		Building Materials			**74,605**	**1,270,949**
7	2420	Cement, Lime and Plaster	0.812	2.159	5,557	175716
7	2436	Ready mixed concrete	1.021	2.159	32,868	186203
7	2437	Other Building products of concrete, cement or plaster	1.021	2.159	33,272	791017
7	2440	Asbestos Goods	0.972	2.159	2,908	118013
		Miscellaneous Manufacturing			**286,521**	**6,752,143**
8	2514	synthetic resins and plastic materials	0.813	0.845	42,927	748797
8	2570	Pharmaceutical Products	0.763	0.845	18,782	1919827
8	4130	Preparation of milk and milk products	0.769	0.845	16,295	921438
8	4283	Soft Drinks	0.807	0.845	10,629	491175
8	4671	Wooden and upholstered furniture	0.765	0.845	197,888	2670906
		Bread and Biscuits			**124,819**	**3,765,286**
9	4196	Bread and flour confectionary	1.32	2.851	116,311	2869687
9	4197	Biscuits and crispbread	1.32	2.851	8,508	895599
		Large transport Manufacturing			**50,524**	**1,472,255**

10	3610	Shipbuilding and repairing	1.523	2.284	50,524	1472255
		Soaps and Perfumes			**17,863**	**942,793**
11	2581	Soap and synthetic detergents	1.11	2.517	6,435	331590
11	2582	Perfumes, cosmetics and toilet preparations	1.11	2.517	11428	611203
		Grain and Starch			**4995**	**207010**
12	4160	Grain Milling	1.002	2.09	4684	175879
12	4180	Starch	1.002	2.09	311	31131
		Pet feeds			**21219**	**517638**
13	4221	Compound animal feeds	1.088	2.599	14903	313396
13	4222	Pet foods and non-compound animal feeds	1.088	2.599	6316	204242
		Leather working			**27284**	**359714**
14	4410	Leather and Fellmongery	0.913	2.199	6221	142957
14	4420	Leather Goods	0.913	2.199	21063	216757
		Paints			**20353**	**708192**
15	2551	Paints, varnishes and painters' fillings	0.978	2.368	15561	588212
15	2552	Printing ink	0.978	2.368	4792	119980
		Processing of food stuffs			**24743**	**1234801**
16	4147	Processing of fruit and vegetables	0.735	2.262	12697	631183
16	4150	Fish processing	0.735	2.262	12046	603618
		Explosives and ordnance			**6032**	**583749**
17	2565	explosives	0.793	1.963	1128	81613
17	3290	Ordnance, small arms and ammunition	0.793	1.963	4904	502136
		Cooking fats and oils			**2254**	**121515**
18	4115	Margarine and compound cooking fats	0.882	1.925	528	55877
18	4116	Processing organic oils and fats	0.882	1.925	1726	65638
		Processing meats			**37412**	**2736954**
19	4122	Bacon curing and meat processing	1.03	2.463	27008	1845612
19	4123	Poultry slaughter and processing	0.887	2.463	5818	744067
19	4126	Animal by-product processing	1	2.463	4586	147275
		Sugar			**579**	**109309**

20	4200	Sugar and sugar by-products	1.523	2.284	579	109309
		Confectionary			**57135**	**2877066**
21	4213	Ice cream	1.22	2.714	8469	165414
21	4214	Cocoa, chocolate and sugar confectionary	1.254	2.714	12069	992158
21	4239	Miscellaneous foods	1.208	2.714	36597	1719494
		Paper Products			**78362**	**2483328**
22	4722	Household and personal hygiene products of paper	0.805	2.191	4282	331742
22	4723	Stationary	0.99	2.191	26971	534886
22	4724	Packaging products of paper and pulp	0.741	2.191	6241	225776
22	4725	Packaging products of board	1.006	2.191	27059	1119836
22	4728	Other paper and board products	1.035	2.191	13809	271088
		Printing products			**771320**	**9434424**
23	4751	Printing and publishing of periodicals	1.191	2.388	40566	1974242
23	4752	Printing and publishing of newspapers	1.24	2.388	82051	1489226
23	4753	Printing and publishing of books	1.192	2.388	87537	1031894
23	4754	Other printing and publishing	1.198	2.388	561166	4939062
		Distilling and compounding			**6575**	**348332**
24	4240	Distilling and compounding	1.523	2.284	6575	348332
		Brewing and Tobacco			**19670**	**1091137**
25	4261	Wines, cider and perry	0.545	1.807	3320	103306
25	4270	Brewing and malting	0.657	1.807	15194	734057
25	4290	Tobacco Industry	0.444	1.807	1156	253774
		Recreational Manufacturing			**318502**	**2319685**
26	4910	Jewellery and coins	1.006	2.228	59163	333469
26	4920	Musical instruments	1.067	2.228	8047	58640
26	4941	Toys and games	0.899	2.228	18064	224007
26	4942	Sport goods	1.069	2.228	16778	201881
26	4959	Other manufacturing NES	1.128	2.228	216450	1501688
		Precision Apparatus			**95,291**	**1,978,970**
27	3710	Measuring, checking, and precision instruments and apparatus	1.054	2.187	36,155	848390

27	3720	Medical and Surgical Equipment and Orthopaedic Appliances	1.033	2.187	46,540	859081
27	3732	Optical Precision instruments	0.942	2.187	3,088	103051
27	3733	Photographic and cinematographic equipment	0.924	2.187	4,708	109096
27	3740	Clock, watches and other timing devices	0.736	2.187	4,800	59352
		Inorganic and organic chemicals			**22,231**	**1,527,666**
28	2511	Inorganic chemicals except industrial gases	0.527	1.805	6,358	299901
28	2512	Basic organic chemicals except specialised pharmaceutical chemicals	0.821	1.805	8,521	789490
28	2513	fertilisers	0.584	1.805	4,020	135969
28	2516	Dyestuffs and pigments	0.616	1.805	3,332	302306
		Essential oils			**2,121**	**86,875**
29	2564	essential oils and flavouring materials	1.523	2.284	2,121	86875
		Chemical and Adhesives			**36,932**	**1,158,463**
30	2562	formulated adhesives and sealants	0.896	2.07	5,456	148439
30	2567	Miscellaneous products for industrial use	0.935	2.07	22572	736573
30	2568	Formulated pesticides	0.756	2.07	2,654	130831
30	2599	Chemical products NES	0.949	2.07	6250	142620
		Man Made Fibres			**1012**	**152368**
31	2600	Productions of man-made fibres	1.523	2.284	1012	152368
		Rubber tyres			**2,282**	**421318**
32	4811	Rubber tyres and inner tubes	1.523	2.284	2,282	421318
		Plastic and rubber products			**207,927**	**5,771,510**
33	4812	Other rubber products	1.185	2.574	21,621	857292
33	4832	Plastics semi-manufactures	1.19	2.574	20,859	841547
33	4834	Plastics Building products	1.186	2.574	47,644	1091221
33	4835	Plastics packaging products	1.19	2.574	22,604	955008
33	4836	Plastics products NES	1.242	2.574	95,199	2026442
		Electronic Equipment			**231,853**	**6,285,035**
34	3302	Electronic data processing equipment	0.895	2.054	61,160	1165655
34	3410	Insulted wires and cables	0.835	2.054	12,115	606332

34	3420	Basic electrical equipment	0.994	2.054	68,550	2308459
34	3432	Batteries and accumulators	0.439	2.054	5,415	193384
34	3433	Alarms and signalling equipment	0.978	2.054	35,500	582900
34	3460	Domestic-type electronic appliances	0.769	2.054	14,142	759483
34	3470	Electric lamps and other electric lighting equipment	0.921	2.054	34,971	668822
		Wood manufacturing			**301,682**	**3,829,048**
35	4610	Sawmilling, planning etc of wood	1.021	2.071	38,461	448362
35	4620	Manufacturing of semi-finished wood products and further processing and treatment of wood	0.825	2.071	7,200	166995
35	4630	Builders' carpentry and joinery	1.02	2.071	129,001	1199215
35	4640	Wooden containers	1.018	2.071	26,592	265136
35	4650	Other wooden articles (except furniture)	1.012	2.071	46,310	283842
35	4663	Brushes and brooms	0.836	2.071	3,514	114731
35	4672	Shop and office fitting	0.983	2.071	37,452	654798
35	4710	Pulp, paper and board	0.913	2.071	13,152	695969
		Wall Coverings			**1,484**	**109,333**
36	4721	Wall Coverings	1.523	2.284	1,484	109333
		Synthetic rubber			**532**	**37758**
37	2515	synthetic rubber	1.523	2.284	532	37758
		Tractors			**1,368**	**171,019**
38	3212	Wheeled tractors	1.523	2.284	1,368	171019
		Vehicles			126,912	6,863,115
39	3211	Agricultural machinery	0.646	1.906	30,898	262858
39	3510	Motor vehicles and their engines	0.832	1.906	17,305	3151176
39	3521	Motor vehicles bodies	0.784	1.906	12,421	356401
39	3522	Trailers and semi-trailers	0.787	1.906	8,064	236692
39	3523	Caravans	0.481	1.906	3,702	160817
39	3530	Motor Vehicle parts	0.839	1.906	49,583	2511957
39	3633	Motor cycles and parts	0.398	1.906	2,336	114570
39	3634	Pedal cycles and parts	0.701	1.906	2,603	68644

		Textiles			**84,866**	**2,420,896**
40	4310	Woollen and worsted Industry	1.039	2.256	14,578	614680
40	4322	Weaving of cotton, silk and man-made fibres	1.017	2.256	12,536	364805
40	4370	Textile finishing	1.132	2.256	20,262	449319
40	4384	Pile carpets, carpeting and rugs	0.936	2.256	9,514	369081
40	4395	Lace	1.065	2.256	4,282	63610
40	4398	Narrow fabrics	0.874	2.256	6,084	169101
40	4557	Household textiles	1.045	2.256	17,610	390300
		Other Textiles			**67,277**	**685,908**
41	4396	Rope, twine and net	0.532	1.942	3,976	59005
41	4399	Other Miscellaneous textiles	0.665	1.942	10,027	114023
41	4555	Soft furnishings	0.861	1.942	26,163	330096
41	4556	Canvas goods, sacks and other made-up textiles	0.925	1.942	27,111	182784
		Clothing			**230,662**	**5,015,377**
42	4363	Hosiery and other weft knitted goods and fabrics	0.77	2.137	32,912	1168540
42	4510	Footwear	0.685	2.137	17,336	733250
42	4532	Men's and boy's tailored outerwear	1.062	2.137	25,710	582185
42	4534	Work clothing and men's and boy's jeans	0.873	2.137	12,258	289969
42	4535	Men's and boy's shirts, underwear and nightwear	0.663	2.137	8,573	378284
42	4536	Women's and girl's light outerwear, lingerie and infants' wear	1.056	2.137	112,777	1578529
42	4539	Other dress industries	1.055	2.137	21,096	284620
		Metal and Chemical Machinery			**421,863**	**6,442,840**
43	3169	Finished metal products NES	1.221	2.43	199,150	2192310
43	3221	Metal-working machine tools	1.182	2.43	57,062	620660
43	3222	Engineers' small tools	1.175	2.43	51,248	756412
43	3245	Chemical industry machinery; furnaces and kilns; gas, water and waste treatment plant	1.065	2.43	11,151	206794
43	3255	Mechanical lifting and handling equipment	1.161	2.43	47,160	1076272
43	3284	Refrigerating machinery, space heating, ventilating and air conditioning equipment	1.18	2.43	44,331	1142509

43	3434	Electrical equipment for motor vehicles, cycles and aircraft	1.009	2.43	11,761	447883
		Commercial Machinery			**70,211**	**2,281,542**
44	3230	Textile Machinery	0.52	1.671	9,977	179246
44	3244	Food, drink and tobacco processing machinery; packaging and bottling machinery	0.727	1.671	15,252	412964
44	3254	Construction and earth moving equipment	0.494	1.671	9,882	386663
44	3275	Machinery for working wood, rubber, plastics, leather and making paper, glass, bricks and similar materials; laundry and dry cleaning machinery	0.452	1.671	8,538	204169
44	3281	Internal combustion engines and other prime movers	0.445	1.671	10,860	578666
44	3286	Other Industrial and commercial machinery	0.52	1.671	10,220	287085
44	3301	Office machinery	0.523	1.671	5,482	232749
		Mining machinery			**4,756**	**247,552**
45	3251	Mining machinery	1.523	2.284	4,756	247552
		Other manufacturing			**282,086**	**7,045,327**
46	3276	Printing, bookbinding and paper goods machinery	1.1	2.161	59,193	823355
46	3283	Compressors and fluid power equipment	1.051	2.161	12,680	526546
46	3441	Telegraph and telephone apparatus and equipment	1.068	2.161	21,218	816203
46	3442	Electrical instruments and control systems	1.108	2.161	26,908	768353
46	3443	Radio and electronic capital goods	1.018	2.161	50,347	1790172
46	3452	Gramophone records and pre-recorded tapes	0.944	2.161	53,886	242952
46	3453	Active components and electronic sub-assemblies	1.075	2.161	25,398	1019738
46	3454	Electronic consumer goods and other electronic goods NES	1.136	2.161	23,388	571985
46	3620	Railway and tramways	0.984	2.161	9,068	486023

Table A.7.2 Cluster configuration with Industry names and plant count

A.8 Algorithm Changed Cluster Configuration

Cluster	Industry Code	Industry Name	WCRi	WCRc	Number of plants	Total Employment
		Ferrous metals and manufacturing			**47,337**	**2,730,136**
1	2210	Iron and Steel Industry	0.803	2.219	6,028	1152141
1	2220	Steel Tubes	1.039	2.219	8,568	415496
1	2234	Drawing and manufacture of steel wire and steel wire products	1.041	2.219	13,643	382177
1	2235	Other drawing, cold rolling, and cold forming	0.933	2.219	4,486	117459
1	3111	Ferrous metal foundries	1.021	2.219	14,612	662863
		Non-ferrous metal Manufacturing			**144,130**	**3,432,349**
2	2245	Aluminium and aluminium alloys	1.011	2.075	8,350	370047
2	2246	Copper, brass and other copper alloys	0.861	2.075	4,789	221895
2	2247	Other Non-ferrous metals and their alloys	0.855	2.075	8,470	280083
2	3112	Non-ferrous metal foundries	1.08	2.075	11,607	391827
2	3120	Forging, pressing and stamping	1.107	2.075	44,673	993151
2	3137	Bolts, nuts etc; Springs; Non Precision chains	1.017	2.075	20,685	484896
2	3138	Heat and surface Metal treatment, including sintering	1.11	2.075	45,556	690450
		Metal Manufacturing			**576,072**	**8,062,183**
3	3142	Metal Doors, Windows etc	0.977	2.012	35,142	525066
3	3162	Cutlery, spoons, forks and similar table ware, razors	0.387	2.012	2,230	75257
3	3164	Packaging products of metal	0.721	2.012	9,055	465532
3	3165	Domestic heating and cooking appliances (non electrical)	0.458	2.012	4,562	214811
3	3204	Fabricated constructional steelwork	0.998	2.012	63,683	1393796
3	3205	Boilers and process plant fabrications	0.913	2.012	36,801	797515
3	3261	Precision chains and other mechanical power transmission equipment	0.949	2.012	44,785	585878
3	3287	Pumps	0.877	2.012	12,667	428039
3	3288	Industrial valves	0.795	2.012	8,326	429356
3	3289	Mechanical, marine and precision engineering NES	1.012	2.012	358,821	3146933

		Mineral Extraction			**24,751**	**882,671**
4	2330	Salt Extraction and Refining	0.702	1.809	263	15024
4	2489	Ceramic goods	0.702	1.809	24,488	867647
		Other Minerals extraction			**2,759**	**53,638**
5	2396	Extraction of other minerals	1.522	2.282	2,759	53638
		Mineral Manufacturing			**135,839**	**2,564,540**
6	2410	Structural Clay Products	0.825	2.005	9,446	348336
6	2450	Working of Stone and other Non Metallic minerals	0.894	2.005	74,034	882447
6	2460	Abrasive Products	0.856	2.005	7,735	128831
6	2471	Flat glass	0.94	2.005	18,545	479806
6	2478	glass containers	0.625	2.005	3,007	208356
6	2479	other glass products	0.803	2.005	17,284	329938
6	2481	Refractory good	0.792	2.005	5,788	186826
		Building Materials			**74,605**	**1,270,949**
7	2420	Cement, Lime and Plaster	0.81	2.15	5,557	175716
7	2436	Ready mixed concrete	1.02	2.15	32,868	186203
7	2437	Other Building products of concrete, cement or plaster	1.019	2.15	33,272	791017
7	2440	Asbestos Goods	0.97	2.15	2,908	118013
		Miscellaneous Manufacturing			**286,521**	**6,752,143**
8	2514	synthetic resins and plastic materials	0.812	0.842	42,927	748797
8	2570	Pharmaceutical Products	0.762	0.842	18,782	1919827
8	4130	Preparation of milk and milk products	0.768	0.842	16,295	921438
8	4283	Soft Drinks	0.806	0.842	10,629	491175
8	4671	Wooden and upholstered furniture	0.764	0.842	197,888	2670906
		Bread and Biscuits			**124,819**	**3,765,286**
9	4196	Bread and flour confectionary	1.319	2.843	116,311	2869687
9	4197	Biscuits and crispbread	1.319	2.843	8,508	895599
		Large transport Manufacturing			**78,881**	**5,226,903**
10	3640	Aerospace equipment manufacturing and repairing	0.818	1.355	28,357	3754648

10	3610	Shipbuilding and repairing	0.818	1.355	50,524	1472255
		Soaps and Perfumes			**17,863**	**942,793**
11	2581	Soap and synthetic detergents	1.108	2.509	6,435	331590
11	2582	Perfumes, cosmetics and toilet preparations	1.108	2.509	11428	611203
		Grain and Starch			**4995**	**207010**
12	4160	Grain Milling	1	2.082	4684	175879
12	4180	Starch	1	2.082	311	31131
		Pet feeds			**21219**	**517638**
13	4221	Compound animal feeds	1.087	2.591	14903	313396
13	4222	Pet foods and non-compound animal feeds	1.087	2.591	6316	204242
		Leather working			**27284**	**359714**
14	4410	Leather and Fellmongery	0.912	2.19	6221	142957
14	4420	Leather Goods	0.912	2.19	21063	216757
		Paints			**20353**	**708192**
15	2551	Paints, varnishes and painters' fillings	0.977	2.36	15561	588212
15	2552	Printing ink	0.977	2.36	4792	119980
		Processing of food stuffs			**24743**	**1234801**
16	4147	Processing of fruit and vegetables	0.734	2.254	12697	631183
16	4150	Fish processing	0.734	2.254	12046	603618
		Explosives and ordnance			**6032**	**583749**
17	2565	explosives	0.791	1.954	1128	81613
17	3290	Ordnance, small arms and ammunition	0.791	1.954	4904	502136
		Cooking fats and oils			**2254**	**121515**
18	4115	Margarine and compound cooking fats	0.881	1.917	528	55877
18	4116	Processing organic oils and fats	0.881	1.917	1726	65638
		Processing meats			**37412**	**2736954**
19	4122	Bacon curing and meat processing	1.029	2.454	27008	1845612
19	4123	Poultry slaughter and processing	0.885	2.454	5818	744067
19	4126	Animal by-product processing	0.998	2.454	4586	147275
		Sugar			**579**	**109309**

20	4200	Sugar and sugar by-products	1.522	2.282	579	109309
		Confectionary			**57135**	**2877066**
21	4213	Ice cream	1.219	2.707	8469	165414
21	4214	Cocoa, chocolate and sugar confectionary	1.253	2.707	12069	992158
21	4239	Miscellaneous foods	1.207	2.707	36597	1719494
		Paper Products			**78362**	**2483328**
22	4722	Household and personal hygiene products of paper	0.802	2.183	4282	331742
22	4723	Stationary	0.988	2.183	26971	534886
22	4724	Packaging products of paper and pulp	0.739	2.183	6241	225776
22	4725	Packaging products of board	1.005	2.183	27059	1119836
22	4728	Other paper and board products	1.033	2.183	13809	271088
		Printing products			**771320**	**9434424**
23	4751	Printing and publishing of periodicals	1.19	2.38	40566	1974242
23	4752	Printing and publishing of newspapers	1.239	2.38	82051	1489226
23	4753	Printing and publishing of books	1.191	2.38	87537	1031894
23	4754	Other printing and publishing	1.198	2.38	561166	4939062
		Distilling and compounding			**6575**	**348332**
24	4240	Distilling and compounding	1.522	2.282	6575	348332
		Brewing and Tobacco			**19670**	**1091137**
25	4261	Wines, cider and perry	0.543	1.797	3320	103306
25	4270	Brewing and malting	0.654	1.797	15194	734057
25	4290	Tobacco Industry	0.441	1.797	1156	253774
		Recreational Manufacturing			**318502**	**2319685**
26	4910	Jewellery and coins	1.004	2.22	59163	333469
26	4920	Musical instruments	1.066	2.22	8047	58640
26	4941	Toys and games	0.897	2.22	18064	224007
26	4942	Sport goods	1.068	2.22	16778	201881
26	4959	Other manufacturing NES	1.127	2.22	216450	1501688
		Precision Apparatus			**95,291**	**1,978,970**
27	3710	Measuring, checking, and precision instruments and apparatus	1.053	2.178	36,155	848390

27	3720	Medical and Surgical Equipment and Orthopaedic Appliances	1.032	2.178	46,540	859081
27	3732	Optical Precision instruments	0.94	2.178	3,088	103051
27	3733	Photographic and cinematographic equipment	0.923	2.178	4,708	109096
27	3740	Clock, watches and other timing devices	0.734	2.178	4,800	59352
		Inorganic and organic chemicals			**22,231**	**1,527,666**
28	2511	Inorganic chemicals except industrial gases	0.525	1.797	6,358	299901
28	2512	Basic organic chemicals except specialised pharmaceutical chemicals	0.819	1.797	8,521	789490
28	2513	fertilisers	0.581	1.797	4,020	135969
28	2516	Dyestuffs and pigments	0.614	1.797	3,332	302306
		Essential oils			**2,121**	**86,875**
29	2564	essential oils and flavouring materials	1.522	2.282	2,121	86875
		Chemical and Adhesives			**36,932**	**1,158,463**
30	2562	formulated adhesives and sealants	0.894	2.061	5,456	148439
30	2567	Miscellaneous products for industrial use	0.934	2.061	22572	736573
30	2568	Formulated pesticides	0.754	2.061	2,654	130831
30	2599	Chemical products NES	0.948	2.061	6250	142620
		Man Made Fibres			**1012**	**152368**
31	2600	Productions of man-made fibres	1.522	2.282	1012	152368
		Rubber tyres			**2,282**	**421318**
32	4811	Rubber tyres and inner tubes	1.522	2.282	2,282	421318
		Plastic and rubber products			**207,927**	**5,771,510**
33	4812	Other rubber products	1.183	2.567	21,621	857292
33	4832	Plastics semi-manufactures	1.189	2.567	20,859	841547
33	4834	Plastics Building products	1.185	2.567	47,644	1091221
33	4835	Plastics packaging products	1.189	2.567	22,604	955008
33	4836	Plastics products NES	1.241	2.567	95,199	2026442
		Electronic Equipment			**231,853**	**6,285,035**
34	3302	Electronic data processing equipment	0.893	2.045	61,160	1165655
34	3410	Insulted wires and cables	0.832	2.045	12,115	606332

34	3420	Basic electrical equipment	0.992	2.045	68,550	2308459
34	3432	Batteries and accumulators	0.436	2.045	5,415	193384
34	3433	Alarms and signalling equipment	0.976	2.045	35,500	582900
34	3460	Domestic-type electronic appliances	0.767	2.045	14,142	759483
34	3470	Electric lamps and other electric lighting equipment	0.919	2.045	34,971	668822
		Wood manufacturing			**301,682**	**3,829,048**
35	4610	Sawmilling, planning etc of wood	1.02	2.062	38,461	448362
35	4620	Manufacturing of semi-finished wood products and further processing and treatment of wood	0.823	2.062	7,200	166995
35	4630	Builders' carpentry and joinery	1.019	2.062	129,001	1199215
35	4640	Wooden containers	1.017	2.062	26,592	265136
35	4650	Other wooden articles (except furniture)	1.011	2.062	46,310	283842
35	4663	Brushes and brooms	0.834	2.062	3,514	114731
35	4672	Shop and office fitting	0.981	2.062	37,452	654798
35	4710	Pulp, paper and board	0.913	2.071	13,152	695969
		Wall Coverings			**1,484**	**109,333**
36	4721	Wall Coverings	0.911	2.062	1,484	109333
		Synthetic rubber			**532**	**37758**
37	2515	synthetic rubber	1.522	2.282	532	37758
		Tractors			**1,368**	**171,019**
38	3212	Wheeled tractors	1.522	2.282	1,368	171019
		Vehicles			126,912	6,863,115
39	3211	Agricultural machinery	0.646	1.906	30,898	262858
39	3510	Motor vehicles and their engines	0.832	1.906	17,305	3151176
39	3521	Motor vehicles bodies	0.784	1.906	12,421	356401
39	3522	Trailers and semi-trailers	0.787	1.906	8,064	236692
39	3523	Caravans	0.481	1.906	3,702	160817
39	3530	Motor Vehicle parts	0.839	1.906	49,583	2511957
39	3633	Motor cycles and parts	0.398	1.906	2,336	114570

39	3634	Pedal cycles and parts	0.701	1.906	2,603	68644
		Textiles			**84,866**	**2,420,896**
40	4310	Woollen and worsted Industry	1.039	2.256	14,578	614680
40	4322	Weaving of cotton, silk and man-made fibres	1.017	2.256	12,536	364805
40	4370	Textile finishing	1.132	2.256	20,262	449319
40	4384	Pile carpets, carpeting and rugs	0.936	2.256	9,514	369081
40	4395	Lace	1.065	2.256	4,282	63610
40	4398	Narrow fabrics	0.874	2.256	6,084	169101
40	4557	Household textiles	1.045	2.256	17,610	390300
		Other Textiles			**67,277**	**685,908**
41	4396	Rope, twine and net	0.532	1.942	3,976	59005
41	4399	Other Miscellaneous textiles	0.665	1.942	10,027	114023
41	4555	Soft furnishings	0.861	1.942	26,163	330096
41	4556	Canvas goods, sacks and other made-up textiles	0.925	1.942	27,111	182784
		Clothing			**230,662**	**5,015,377**
42	4363	Hosiery and other weft knitted goods and fabrics	0.77	2.137	32,912	1168540
42	4510	Footwear	0.685	2.137	17,336	733250
42	4532	Men's and boy's tailored outerwear	1.062	2.137	25,710	582185
42	4534	Work clothing and men's and boy's jeans	0.873	2.137	12,258	289969
42	4535	Men's and boy's shirts, underwear and nightwear	0.663	2.137	8,573	378284
42	4536	Women's and girl's light outerwear, lingerie and infants' wear	1.056	2.137	112,777	1578529
42	4539	Other dress industries	1.055	2.137	21,096	284620
		Metal and Chemical Machinery			**421,863**	**6,442,840**
43	3169	Finished metal products NES	1.221	2.43	199,150	2192310
43	3221	Metal-working machine tools	1.182	2.43	57,062	620660
43	3222	Engineers' small tools	1.175	2.43	51,248	756412
43	3245	Chemical industry machinery; furnaces and kilns; gas, water and waste treatment plant	1.065	2.43	11,151	206794
43	3255	Mechanical lifting and handling equipment	1.161	2.43	47,160	1076272

43	3284	Refrigerating machinery, space heating, ventilating and air conditioning equipment	1.18	2.43	44,331	1142509
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44	3286	Other Industrial and commercial machinery	0.52	1.671	10,220	287085
44	3301	Office machinery	0.523	1.671	5,482	232749
		Mining machinery			**4,756**	**247,552**
45	3251	Mining machinery	1.523	2.284	4,756	247552
		Other manufacturing			**282,086**	**7,045,327**
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46	3283	Compressors and fluid power equipment	1.051	2.161	12,680	526546
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46	3452	Gramophone records and pre-recorded tapes	0.944	2.161	53,886	242952
46	3453	Active components and electronic sub-assemblies	1.075	2.161	25,398	1019738
46	3454	Electronic consumer goods and other electronic goods NES	1.136	2.161	23,388	571985
46	3620	Railway and tramways	0.984	2.161	9,068	486023

Table A.8.1 Algorithm Changed Cluster Configuration

A.8.1 Cluster configuration using 1974-75 Input-Output Employment data

Cluster	Cluster name	WCR_c Score
1	Agriculture	4.353
2	Food Stuffs	0.847
3	Home Chemicals	0.501
4	Soft drinks and Catering	4.119
5	Textiles	0.864
6	Animal Processing	1.590
7	Water Transport	-
8	Chemicals	0.688
9	Mining and Energy	0.760
10	Coke and Iron	2.350
11	Railways	-
12	Building and Construction	1.986
13		0.347
14	Supply Services	1.036
15	Air transport	-
16	Gas	4.671
17	Clothing	4.076
18	Household Materials	0.848
19	Metal Manufacturing	0.819
20	Vehicles	0.722
21	Office Machinery	2.884
22	Electronic Machinery	0.804

Table A.8.2 The UK Cluster configuration using 1974/75 data

A.9 National Cluster Count Tables

A.9.1 National Plant Count Tables by ownership type

CLUSTER	UK	EU	US	ROW
1	44,778	1,197	905	457
2	139,868	1,893	1,447	922
3	589,761	6,831	5,697	2,139
4	24,084	305	337	*
5	2,626	82	*	*
6	128,043	5,690	871	1,235
7	65,970	4,802	202	3,631
8	277,669	4,624	3,209	1,019
9	123,653	791	215	160
10	49,893	386	159	86
11	16,342	406	915	210
12	4,533	201	224	37
13	20,400	550	186	*
14	27,188	29	39	*
15	16,462	2,404	830	657
16	23,723	523	184	313
17	5,629	290	81	*
18	2,017	92	133	*
19	35,729	1,086	446	151
20	571		*	
21	53,746	1,580	1,477	332
22	73,459	2,801	1,542	560
23	758,860	4,544	5,224	2,691
24	5,282	554	125	614
25	18,713	427	355	175
26	315,615	1,293	1,057	537
27	89,876	2,185	2,677	553
28	19,069	1,719	1,167	276
29	1,793	115	180	*
30	31,830	2,026	2,801	275
31	859	51	88	*
32	1,630	479	*	*
33	198,585	5,045	3,032	1,265
34	220,653	4,655	4,971	1,573
35	298,706	1,951	705	320
36	1,340	63	*	*
37	336	120	56	*
38	1,204	58	93	*
39	119,625	2,559	3,574	1,154
40	83,094	921	574	277
41	66,667	396	140	74
42	228,821	622	820	399
43	409,591	5,970	4,939	1,363

44	65,890	1,582	2,145	594
45	4,274	105	357	*
46	267,145	6,391	5,804	2,746

Table A.9.1 National Plant Count Tables by ownership type

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.9.2 National Average employment figures by ownership type

CLUSTER	UK	EU	US	ROW
1	2,308,990	165,300	109,186	146,660
2	2,870,663	182,200	199,997	179,490
3	10,100,000	738,204	682,240	306,938
4	751,387	85,345	43,049	*
5	40,203	4,600	*	*
6	2,176,053	242,158	100,814	45,514
7	1,068,796	154,906	14,380	32,867
8	5,422,220	585,286	656,037	88,600
9	3,474,896	188,505	57,456	44,430
10	1,352,121	59,403	57,325	3,406
11	633,346	61,722	214,955	32,770
12	163,384	19,020	22,899	1,708
13	429,363	37,450	46,040	*
14	356,892	789	1,273	*
15	475,799	147,575	59,605	25,213
16	1,046,205	67,909	29,684	91,003
17	513,643	58,137	10,893	*
18	95,952	8,761	16,020	*
19	2,303,822	256,362	127,340	49,430
20	107,934		*	
21	1,951,516	364,437	496,343	64,769
22	1,890,774	282,548	247,266	62,741
23	8,342,000	278,020	502,017	312,378
24	277,969	27,822	7,962	34,579
25	889,077	78,574	93,740	29,747
26	2,093,182	74,878	118,310	33,316
27	1,451,912	157,058	318,798	51,201
28	1,141,412	203,508	150,624	32,122
29	56,250	10,108	19,110	*
30	722,562	170,450	245,582	19,869
31	115,354	7,268	28,072	1,674
32	95,846	183,259	109,047	33,166
33	4,858,029	442,566	334,369	136,544
34	4,657,351	612,615	777,913	237,155
35	3,472,544	205,396	89,727	61,380
36	82,863	9,980	*	*
37	10,132	14,160	11,799	*
38	41,486	30,341	77,895	*

39	3,709,469	782,403	1,828,940	542,303
40	2,251,363	66,812	76,466	26,255
41	645,888	24,936	10,585	4,498
42	4,794,612	50,814	112,038	57,914
43	5,458,461	420,192	470,583	93,604
44	1,552,839	231,474	390,949	106,279
45	183,677	5,907	56,381	*
46	5,132,687	678,752	751,941	481,949

Table A.9.2 National Average employment figures by ownership type

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.9.3 National Plant Count over three decades 1984-1993, 1994-2003, and 2004-2014

CLUSTER	1984-1993	1994-2003	2004-2014
1	14,769	18,439	14,129
2	53,450	51,437	39,243
3	158,911	212,378	233,140
4	8,409	10,607	5,735
5	2,146	273	340
6	35,253	53,405	47,181
7	26,584	26,046	21,975
8	84,605	98,380	103,536
9	46,779	45,772	32,268
10	16,796	16,941	16,787
11	5,458	6,165	6,250
12	1,887	1,735	1,373
13	7,603	7,991	5,625
14	13,378	8,702	5,204
15	6,008	8,248	6,097
16	7,008	9,232	8,503
17	1,790	2,132	2,110
18	891	809	554
19	12,520	12,319	12,573
20	260	218	101
21	18,679	19,351	19,105
22	30,705	27,777	19,880
23	216,508	294,103	260,709
24	2,103	2,141	2,331
25	4,585	6,799	8,286
26	89,787	137,699	91,016
27	27,160	27,570	40,561
28	6,920	9,960	5,351
29	741	723	657
30	11,023	14,683	11,226
31	388	443	181
32	898	849	535
33	57,590	77,784	72,553
34	67,142	81,499	83,212

35	94,140	105,394	102,148
36	517	771	196
37	216	189	127
38	491	767	110
39	36,894	48,374	41,644
40	29,625	29,188	26,053
41	18,551	16,995	31,731
42	100,882	83,806	45,974
43	152,450	148,348	121,065
44	28,910	23,854	17,447
45	1,943	1,651	1,162
46	50,180	98,014	133,892

Table A.9.3 National Plant Count over three decades 1984-1993, 1994-2003, and 2004-2014

A.9.4 National total employment over three decades 1984-1993, 1994-2003, and 2004-2014

CLUSTER	1984-1993	1994-2003	2004-2014
1	1323727	877898	528511
2	1408211	1212799	811340
3	4324524	3824724	3667583
4	440754	314967	126950
5	31740	5448	16450
6	1043506	846634	674400
7	522856	396023	352070
8	2407083	2362800	1982261
9	1485063	1244576	1035648
10	700428	389345	382482
11	338018	353020	251756
12	76498	67837	62675
13	208378	174090	135170
14	193109	115219	51386
15	280663	246093	181436
16	427847	409857	397096
17	242038	155784	185926
18	60772	41054	19689
19	973281	894952	868721
20	64605	28529	16175
21	1091787	954264	831015
22	1124254	819150	539925
23	3039047	3403153	2992224
24	144782	106371	97179
25	534233	345101	211804
26	637597	1201774	480316
27	757822	438563	782585
28	695794	568641	263231
29	31864	28193	26818
30	421759	433267	303437
31	96950	42499	12919
32	219821	141197	60300
33	1914010	2132013	1725486
34	2582895	2327224	1374917
35	1414650	1309465	1104933
36	54504	40419	14410

37	16194	12187	9377
38	104222	51734	15063
39	2701602	2461391	1700122
40	1162164	832342	426390
41	240994	211995	232918
42	2888220	1694860	432298
43	2725653	2227677	1489510
44	1105101	670763	505677
45	144070	57073	46409
46	2835616	2493251	1716462

Table A.9.4 National total employment over three decades 1984-1993, 1994-2003, and 2004-2014

A.10 North East Cluster Count Tables

A.10.1 Plant count and total employment by cluster for the North East of England

CLUSTER	NUMBER OF PLANTS	EMPLOYMENT
1	1,976	220689
2	4,180	147853
3	21,094	542585
4	495	3317
5	146	12212
6	5,325	168983
7	2,803	45445
8	9,100	419921
9	6,562	198890
10	1,575	150957
11	588	64787
12	85	2338
13	325	3917
14	431	5730
15	804	72737
16	798	26467
17	183	46519
18	35	538
19	1,468	93073
20	*	*
21	2,095	133846
22	2,196	128479
23	15,588	235504
24	56	211
25	719	59565
26	8,221	68708
27	2,613	61264
28	1,445	276354
29	42	624
30	1,524	64617
31	41	7275
32	84	3073
33	7,917	385490
34	7,175	436662
35	9,906	184302
36	74	4788
37	*	*
38	*	*
39	3,759	596035
40	1,369	46737
41	2,070	31062
42	3,815	206146
43	11,960	301490
44	2,003	125971
45	315	16308
46	7,398	260625

Table A.10.1 Plant count and total employment by cluster for the North East of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.10.2 Plant count by cluster in the North East of England by the Ownership type

CLUSTER	UK	EU	US	ROW
1	1,829	71	76	*
2	4,035	67	39	39
3	20,400	349	227	118
4	495	*	*	*
5	146	*		*
6	4,926	267	132	*
7	2,564	226	13	*
8	8,559	341	164	36
9	6,470	56	36	*
10	1,575	*		*
11	500	*	88	*
12	85		*	
13	325	*		
14	431			
15	629	120	55	*
16	798	*	*	*
17	183	*		
18	35			
19	1,415	53	*	*
20				
21	2,030	65	*	*
22	1,987	136	73	*
23	15,364	97	127	*
24	56			
25	719	*	*	*
26	8,201	*	20	*
27	2,471	71	71	*
28	1,146	129	170	*
29	42			*
30	1,266	63	195	*
31	41		*	
32	84	*	*	*
33	7,278	354	203	82
34	6,611	263	214	87
35	9,759	108	39	*
36	74	*		
37	*			
38	*			
39	3,238	141	198	182
40	1,369	*	*	
41	2,070	*		
42	3,815	*	*	*
43	11,383	255	239	83
44	1,869	63	71	*
45	315	*	*	*
46	6,971	202	139	86

Table A.10.2 Plant count by cluster in the North East of England by the Ownership type

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.10.3 Total employment by cluster in the North East of England by the Ownership type

	UK	EU	US	ROW	FO
1	192609	6658	7382	*	14040
2	90817	9692	2686	16140	28518
3	415483	27081	21022	15448	63551
4	3317	*	*	*	0
5	12212	*		*	0
6	94709	19075	18062	*	37137
7	35843	4801	*	*	4801
8	231391	48521	41127	4617	94265
9	176470	11210	*	*	11210
10	143625	*	3666	*	3666
11	10737	*	27025	*	27025
12	2338		*		0
13	3917	*			0
14	5730				0
15	33661	14774	4764	*	19538
16	26467	*	*	*	0
17	46519	*			0
18	538				0
19	44469	24302	*	*	24302
20	0	0	0	0	0
21	86910	23468	*	*	23468
22	92651	17914	*	*	17914
23	206940	3496	10786	*	14282
24	211				0
25	59565	*	*	*	0
26	57626	*	5541	*	5541
27	35627	7084	5735	*	12818
28	191375	19672	22818	*	42489
29	624			*	0
30	34463	4402	10675	*	15077
31	7275		*		0
32	3073	*	*	*	0
33	211371	44687	30688	11685	87059
34	253264	57695	18209	15795	91699
35	140180	15176	6885	*	22061
36	4788	*			0
37	*				0
38	*				0
39	95695	34907	62219	153044	250170
40	46737	*	*		0
41	31062	*			0
42	206146	*	*	*	0
43	191483	17860	29504	7640	55003
44	60182	19238	13657	*	32894
45	16308	*	*	*	0
46	155131	36106	7884	8757	52747

Table A.10.3 Total employment by cluster in the North East of England by the Ownership type

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.10.4 Plant count over three decades 1984-1993, 1994-2003, and 2004-2014

CLUSTER	1984-1993	1994-2003	2004-2014
1	591	829	586
2	1,288	1,538	1,354
3	5,260	7,158	8,676
4	140	247	130
5	130	*	26
6	1,512	2,063	1,799
7	1,049	992	969
8	2,584	2,900	3,616
9	2,245	2,597	1,726
10	712	517	399
11	199	209	192
12	26	40	30
13	124	131	82
14	185	146	100
15	213	332	273
16	249	339	223
17	52	79	53
18	*	15	17
19	471	551	476
20			
21	824	684	646
22	879	780	559
23	4,444	5,797	5,517
24	*	14	37
25	199	295	275
26	2,224	3,585	2,442
27	726	811	1,084
28	421	656	395
29	*	19	22
30	466	526	536
31	25	23	*
32	44	38	31
33	1,882	2,948	3,087
34	2,122	2,460	2,593
35	3,188	3,374	3,362
36	30	43	*
37		*	*
38	*	*	*
39	1,047	1,381	1,331
40	376	481	558
41	401	539	1,141
42	1,616	1,442	825
43	3,866	4,055	4,039
44	705	729	605
45	181	107	55
46	1,381	2,488	3,529

Table A.10.4 Plant count over three decades 1984-1993, 1994-2003, and 2004-2014

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.10.5 Total employment over three decades 1984-1993, 1994-2003, and 2004-2014

CLUSTER	1984-1993	1994-2003	2004-2014
1	98880	80246	46139
2	42437	39105	37793
3	198787	163312	155471
4	1006	1457	1698
5	11056	*	9457
6	59334	43142	29950
7	17091	11604	16878
8	111766	114007	99883
9	87931	69705	45345
10	82260	22618	14088
11	16691	13512	7898
12	803	1322	1303
13	1722	1468	864
14	2228	2626	876
15	17546	17764	18016
16	8194	12486	8510
17	22186	13490	10845
18	*	31	103
19	26971	27416	24384
20			
21	45898	41245	39049
22	53650	44388	31720
23	79362	82174	73032
24	*	103	84
25	39503	27634	6139
26	22494	33639	14473
27	19820	13040	15756
28	133508	65004	41775
29	*	286	552
30	17830	17921	15184
31	6851	4198	*
32	4489	6465	2135
33	91353	115835	91242
34	150655	125535	68773
35	56142	55537	50861
36	5083	1118	*
37		*	*
38	*	*	*
39	73944	132838	139083
40	23798	20090	9486
41	9844	8390	13043
42	126358	74178	10914
43	79998	91953	74534
44	38765	27732	35057
45	13699	4550	2651
46	72524	87001	48354

Table A.10.5 Total employment over three decades 1984-1993, 1994-2003, and 2004-2014

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.10.6 Location Quotients for North East based clusters

CLUSTER	LQ PLANT	LQ EMPLOYMENT
1	1.427	1.869
2	0.977	0.787
3	1.176	0.992
4	0.704	0.107
5	1.953	8.684
6	1.333	1.170
7	1.359	0.812
8	1.070	1.092
9	1.773	1.221
10	1.085	1.830
11	1.131	0.915
12	0.647	0.375
13	0.535	0.177
14	0.532	0.361
15	1.354	1.705
16	1.104	0.535
17	1.028	1.805
18	0.523	0.100
19	1.349	0.652
20	0.000	0.000
21	1.270	0.993
22	0.953	1.183
23	0.688	0.563
24	0.287	0.014
25	1.317	1.521
26	0.873	0.689
27	0.927	0.556
28	2.230	3.563
29	0.778	0.226
30	1.394	0.996
31	1.631	1.647
32	1.668	0.704
33	1.283	1.171
34	1.042	1.243
35	1.108	0.961
36	1.839	1.457
37	*	*
38	0.763	0.045
39	0.998	1.141
40	0.562	0.499
41	1.042	1.033
42	0.567	0.955
43	0.955	0.867
44	0.978	1.008
45	2.429	1.912
46		

Table A.10.6 Location Quotients for North East based clusters

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.11 North of England Cluster Count Tables

A.11.1 Plant count and total employment by cluster for the North of England

CLUSTER	COUNT	EMPLOYMENT
1	14,134	1032350
2	30,738	744130
3	148,489	3368613
4	3,534	109036
5	562	19119
6	31,154	808056
7	18,944	330321
8	70,885	2102667
9	38,769	1419530
10	7,379	399581
11	4,594	320290
12	1,242	63325
13	5,668	122048
14	5,145	83493
15	6,131	288610
16	6,427	392326
17	907	164149
18	744	44617
19	10,606	691616
20	*	*
21	15,993	1039688
22	19,603	757130
23	128,032	1829988
24	311	9269
25	4,342	256384
26	67,092	525519
27	19,637	353066
28	8,571	927399
29	520	14589
30	11,055	417089
31	416	57015
32	436	12896
33	53,758	1640990
34	47,983	1467821
35	74,778	1061905
36	656	62019
37	106	4815
38	315	49059
39	29,631	1712230
40	34,427	1359494
41	19,915	295101
42	43,112	1247209
43	94,129	1604449
44	19,547	573678
45	1,369	82226
46	48,694	1192620

Table A.11.1 Plant count and total employment by cluster for the North of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.11.2 Plant count by cluster and ownership type for the North of England

CLUSTER	UK	EU	US	ROW
1	13,197	488	310	139
2	29,750	474	277	237
3	144,791	1,730	1,361	607
4	3,347	38	149	*
5	562	*		*
6	29,051	1,441	356	306
7	16,791	1,161	90	902
8	68,372	1,522	713	278
9	38,337	285	91	56
10	7,296	83	*	*
11	4,151	123	253	67
12	1,063	78	101	*
13	5,538	130	*	*
14	5,145	*	*	
15	4,931	753	262	185
16	6,158	99	50	120
17	907	*	*	*
18	744	*	*	
19	10,197	316	93	*
20	*			
21	15,030	461	416	86
22	18,155	825	492	131
23	125,847	571	1,164	450
24	311			*
25	4,227	115	*	*
26	66,556	243	219	74
27	18,654	407	455	121
28	7,088	817	528	138
29	520	*	*	*
30	9,386	604	1,005	60
31	416	*	*	*
32	436	*	*	*
33	51,156	1,408	820	374
34	45,625	1,184	883	291
35	73,837	580	256	105
36	656	*	*	*
37	106	*	*	
38	237	20	58	
39	27,841	600	846	344
40	33,562	386	365	114
41	19,740	139	36	*
42	42,729	132	195	56
43	91,382	1,300	1,220	227
44	18,429	463	530	125
45	1,316	*	53	*
46	46,046	1,311	929	408

Table A.11.2 Plant count by cluster and ownership type for the North of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.11.3 Total employment by cluster and ownership type for the North of England

CLUSTER	UK	EU	US	ROW
1	869346	66062	30047	66895
2	616504	46149	37483	43994
3	2949855	168699	150410	99649
4	73354	8559	27123	*
5	19119	*	0	*
6	660533	86823	42274	18426
7	280325	34080	7535	8381
8	1732309	190702	148762	30894
9	1267869	104689	36743	10229
10	387512	12069	*	*
11	234624	10262	67428	7976
12	44534	8736	10055	*
13	115582	6466	*	*
14	83493	*	*	0
15	181200	76523	25466	5421
16	332764	16897	14732	27933
17	164149	*	*	*
18	44617	*	*	0
19	591728	85579	14309	*
20	*	0	0	0
21	671490	175338	163767	29093
22	549517	93865	98623	15125
23	1583750	29897	169884	46457
24	9269	0	0	*
25	229046	27338	*	*
26	471492	21332	27433	5262
27	280431	22924	40513	9198
28	702592	132856	72165	19786
29	14589	*	*	*
30	282440	48326	81400	4923
31	57015	*	*	*
32	12896	*	*	*
33	1361278	143091	84609	52012
34	1180456	167995	83638	35732
35	946854	64668	30951	19432
36	62019	*	*	*
37	4815	*	*	
38	8492	2528	38039	
39	914527	155940	435206	206557
40	1281524	24592	47560	5818
41	279967	13072	2062	*
42	1217404	10895	13910	5000
43	1368316	90157	134008	11968
44	426186	54052	72322	21118
45	65842	*	16384	*
46	881959	160549	114640	35472

Table A.11.3 Total employment by cluster and ownership type for the North of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.11.4 Location Quotients by cluster for the North of England

CLUSTER	LQ FOR PLANTS	LQ FOR EMPLOYMENT
1	1.323	1.372
2	0.945	0.787
3	1.089	1.035
4	0.636	0.452
5	0.957	1.878
6	1.016	1.143
7	1.125	0.943
8	1.096	1.130
9	1.377	1.368
10	0.650	0.993
11	1.139	1.233
12	1.103	1.110
13	1.197	0.917
14	0.837	0.848
15	1.335	1.479
16	1.151	1.153
17	0.711	1.071
18	1.724	1.773
19	1.260	0.926
20	0.521	0.265
21	1.241	1.311
22	1.109	1.106
23	0.736	0.704
24	0.210	0.097
25	1.002	0.955
26	0.934	0.822
27	0.913	0.647
28	1.709	2.203
29	1.210	0.759
30	1.327	1.307
31	2.102	1.633
32	1.123	0.465
33	1.146	1.032
34	0.917	0.848
35	1.099	1.006
36	2.216	2.846
37	0.966	0.468
38	1.021	1.041
39	1.035	0.905
40	1.798	2.038
41	1.315	1.573
42	0.828	0.902
43	0.989	0.904

44	1.234	0.912
45	1.317	1.266
46	0.765	0.614

Table A.11.4 Location Quotients by cluster for the North of England

A.12 South East Cluster Count Tables

A.12.1 Plant count and total employment by cluster for the South East of England

CLUSTER	NUMBER OF PLANTS	TOTAL EMPLOYMENT
1	4,056	75915
2	16,037	229995
3	82,739	852873
4	2,133	16012
5	310	3612
6	16,541	203110
7	8,876	149062
8	41,645	963385
9	11,575	246702
10	18,765	637483
11	2,968	160550
12	472	15447
13	1,937	30019
14	1,833	21764
15	2,164	89552
16	1,647	61769
17	1,111	118279
18	183	6306
19	2,584	120212
20	*	*
21	5,536	285847
22	9,540	289210
23	134,717	1359986
24	138	999
25	2,531	82454
26	42,776	307564
27	19,673	463390
28	2,381	87291
29	361	20909
30	5,304	183656
31	*	*
32	149	2826
33	28,563	635383
34	44,251	941475
35	40,651	465382
36	128	4355
37	41	991
38	142	3593
39	15,172	630865
40	5,015	45555
41	7,540	48903
42	9,834	99965
43	58,671	762359

44	8,944	244527
45	287	3529

Table A.12.1 Plant count and total employment by cluster for the South East of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.12.2 Total employment by cluster and ownership type for the South East of England

CLUSTER	UK	EU	US	ROW
1	63376	3821	8717	*
2	199927	4091	10263	15715
3	743685	40273	52613	16302
4	16012	*	*	0
5	3612	0	0	0
6	175081	21243	4845	1941
7	127859	16227	1941	3035
8	668312	85406	202788	6880
9	235137	8864	2700	*
10	547621	58644	31218	*
11	100035	13635	46881	*
12	15447	*	*	*
13	30019	*	*	*
14	21764	0	*	*
15	67349	16654	5549	*
16	61769	*	*	*
17	118279	*	*	*
18	6306	*	*	0
19	118369	1843	*	*
20	*	*	*	*
21	146704	11143	124645	3355
22	184371	24807	70066	9966
23	1232292	40635	74200	12859
24	999	0	*	*
25	82454	*	*	*
26	269646	7422	23974	6521
27	350996	33933	71840	6621
28	54322	7088	25880	*
29	20909	*	*	*
30	98679	13570	71408	*
31	*	0	0	0
32	2681	*	0	145
33	537882	39837	41438	16227
34	680224	69096	159855	32300
35	435194	25734	4454	*
36	4355	*	*	
37	991	*	*	
38	3593	*	*	
39	399105	105781	108784	17196
40	35850	4971	4734	*
41	46157	2745	*	*
42	98290	*	1675	*
43	650173	61787	42196	8203
44	178885	38317	26720	605

45	3529	*	*	*
46	1033406	143265	138552	51961

Table A.12.2 Total employment by cluster and ownership type for the South East of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.12.3 Location Quotients by cluster for the South East of England

CLUSTER	LQ FOR PLANTS	LQ FOR EMPLOYMENT
1	0.617	0.286
2	0.795	0.610
3	1.050	0.977
4	0.627	0.180
5	0.803	0.613
6	0.870	0.721
7	0.850	1.067
8	1.039	1.298
9	0.663	0.599
10	1.809	1.406
11	1.194	1.591
12	0.734	0.866
13	0.667	0.572
14	0.482	0.553
15	0.788	1.214
16	0.502	0.515
17	1.375	1.963
18	0.631	0.513
19	0.501	0.429
20	0.370	0.057
21	0.692	0.904
22	0.870	1.060
23	1.248	1.312
24	0.153	0.028
25	0.959	0.840
26	0.960	1.206
27	1.475	2.130
28	0.776	0.522
29	1.462	2.846
30	1.029	1.444
31	0.028	0.001
32	0.592	0.076
33	0.982	1.002
34	1.364	1.363
35	0.964	1.142
36	0.693	0.479
37	1.249	2.944
38	0.773	0.193
39	0.854	0.836
40	0.423	0.172
41	0.803	0.673

42	0.306	0.184
43	0.994	1.077
44	0.910	0.975
45	0.476	0.143
46	1.347	1.766

Table A.12.3 Location Quotients by cluster for the South East of England

A.13 Underlying figures for the effect of spatial concentration of foreign owned plants within clusters

A.13.1 The effect of the spatial concentration of foreign owned plants within clusters in the North East of England

VARIABLES	FO	FO CITY	EU/ROW/US	EU/ROW/US CITY
INTERMEDIATE INPUTS	0.452***	0.458***	0.401***	0.392***
	6.648	6.848	3.040	3.064
EMPLOYMENT	0.564***	0.562***	0.630***	0.636***
	5.823	5.781	4.959	5.089
CAPITAL	0.201*	0.209**	0.201*	0.209**
	1.905	2.056	1.944	2.065
DI FO	0.00289	0.00127	-	-
	0.327	0.140		
DI UK	-0.0814*	-0.0968*	-0.0894*	-0.107**
	-1.709	-1.898	-1.897	-2.066
DI ROW	-	-	-0.000789	-0.000528
			-0.376	-0.251
DI US	-	-	0.00296	0.00259
			1.054	0.898
DI EU	-	-	0.000125	-0.000218
			0.0334	-0.0627
AGE	-0.331**	-0.338**	-0.382**	-0.390***
	-2.302	-2.444	-2.523	-2.644
MULTI SIC	-0.0571	-0.0587	-0.0461	-0.0426
	-0.967	-0.981	-0.984	-0.947
MULTI REGION	0.142***	0.130**	0.112*	0.108*
	2.794	2.554	1.900	1.908
SINGLE	-0.0822	-0.0939	-0.100*	-0.105*
	-1.426	-1.622	-1.661	-1.731
HERFINDAHL	0.280**	0.275**	0.259	0.250
	2.451	2.404	1.633	1.600
MIDDLESBROUGH	-	0.0112	-	0.0276
		0.533		0.830
SUNDERLAND	-	0.0404	-	0.118**
		0.556		2.564
NEWCASTLE	-	0.0538	-	0.0733
		1.325		1.449
1986	-0.0343*	-0.0326*	-0.0571**	-0.0538*
	-1.754	-1.708	-1.972	-1.880

1987	-0.0231	-0.0259	-0.0195	-0.0229
	-0.935	-1.078	-0.563	-0.662
1988	-0.00284	-0.00307	0.0271	0.0295
	-0.0959	-0.106	0.708	0.757
1989	0.0376	0.0352	0.0540	0.0535
	1.262	1.230	1.086	1.091
1990	0.0240	0.0240	0.00545	0.0240
	1.031	1.031	0.123	1.031
1991	-0.0875*	-0.0931**	-0.0558	-0.0591
	-1.855	-2.037	-1.081	-1.178
1992	-0.0555	-0.0576	-0.0249	-0.0253
	-1.298	-1.385	-0.459	-0.472
1993	-0.0282	-0.0285	-0.00865	-0.00411
	-0.751	-0.782	-0.136	-0.0641
1994	-0.0281	-0.0311	-0.00163	0.00124
	-0.616	-0.700	-0.0288	0.0216
1995	0.0557	0.0516	0.102	0.105
	1.156	1.082	1.608	1.645
1996	0.147***	0.145***	0.173***	0.176***
	3.664	3.741	2.497	2.543
1997	0.146**	0.154**	0.173*	0.189**
	2.205	2.322	1.874	1.976
1998	0.114**	0.101*	0.116	0.114
	2.158	1.926	1.339	1.322
1999	-0.0871	-0.0921	-0.0400	-0.0372
	-1.541	-1.641	-0.490	-0.454
2000	-0.0776	-0.0896	-0.0413	-0.0418
	-1.057	-1.197	-0.466	-0.473
2001	-0.0569	-0.0653	-0.00290	-0.00117
	-0.986	-1.104	-0.0369	-0.0150
2002	0.0202	0.00898	0.0633	0.0619
	0.309	0.135	0.628	0.622
2003	-0.125	-0.123	0.0313	0.0325
	-0.707	-0.702	0.314	0.332
2004	-0.0450	-0.0644	-0.104	-0.108
	-0.387	-0.543	-0.785	-0.816
2005	-0.0685	-0.0736	0.0555	0.0581
	-1.197	-1.283	0.672	0.709
2006	0.0762	0.0662	0.113	0.109
	1.479	1.278	1.351	1.324
2007	0.159*	0.160*	0.278**	0.286**
	1.890	1.893	2	2.073
2008	0.337***	0.336***	0.360**	0.369***
	3.865	3.920	2.553	2.681
2009	0.208**	0.221**	0.320***	0.328***
	2.331	2.558	2.848	3.014
2010	0.354***	0.364***	0.410***	0.428***

	4.380	4.455	3.021	3.138
2011	0.293***	0.295***	0.297***	0.300***
	3.934	3.805	2.759	2.771
2012	0.434***	0.436***	0.443***	0.442***
	4.510	4.699	3.591	3.701
2013	0.393***	0.401***	0.492***	0.499***
	3.770	3.793	3.547	3.656
2014	0.357***	0.365***	0.481***	0.494***
	3.719	3.834	3.178	3.295
CLU 2	0.0824	0.0693	-0.115	-0.115
	0.441	0.390	-1.116	-1.116
CLU 3	0.392	0.383	0.190**	0.190**
	1.619	1.567	1.723	1.723
CLU 4	0.107	0.0907	-	-
	0.419	0.360		
CLU 5	-0.115	-0.106	0.519*	0.519*
	-0.501	-0.475	1.959	1.959
CLU 6	0.256	0.243	0.0886	0.0886
	1.254	1.220	0.877	0.877
CLU 7	0.626**	0.610**	0.547***	0.547***
	2.256	2.209	3.282	3.282
CLU 8	0.203	0.192	0.0104	0.0104
	0.976	0.934	0.125	0.125
CLU 9	-0.0575	-0.0558	-0.390**	-0.390**
	-0.224	-0.218	-2.199	-2.199
CLU 10	0.182	0.178	-0.928***	-0.928***
	0.657	0.644	-2.597	-2.597
CLU 11	-0.124	-0.176	-0.226	-0.226
	-0.389	-0.592	-0.739	-0.739
CLU 12	0.493	0.493	-	-
	1.293	1.293		
CLU 13	0.587**	0.548**	0.681***	0.681***
	2.207	2.085	3.132	3.132
CLU 14	-	0.313	-	-
		0.973		
CLU 15	0.447*	0.439*	0.340**	0.340**
	1.841	1.788	2.538	2.538
CLU 16	0.0341	-0.000472	-0.168	-0.168
	0.154	-0.00218	-1.178	-1.178
CLU 17	0.331	0.319	0.200	0.200
	1.174	1.140	0.830	0.830
CLU 18	-	-	-	-
CLU 19	0.0398	0.0160	-0.163	-0.163
	0.165	0.0679	-1.385	-1.385
CLU 20	-	-	-	-

CLU 21	0.246	0.232	0.0395	0.0395
	1.051	1.020	0.410	0.410
CLU 22	0.184	0.171	0.0215	0.0215
	1.021	0.947	0.259	0.259
CLU 23	0.237	0.225	0.0391	0.0391
	1.065	1.013	0.305	0.305
CLU 24	41.26	37.59	-	-
	0.762	0.698		
CLU 25	0.411*	0.371*	0.397**	0.397**
	1.939	1.793	2.409	2.409
CLU 26	0.219	0.202	-0.0255	-0.0255
	0.999	0.922	-0.226	-0.226
CLU 27	0.371	0.361	0.170	0.170
	1.389	1.283	1.048	1.048
CLU 28	0.140	0.137	0.0839	0.0839
	0.718	0.756	0.674	0.674
CLU 29	0.108	0.0959	-0.285***	-0.285***
	0.485	0.445	-2.694	-2.694
CLU 30	0.390*	0.359*	0.276*	0.276*
	1.867	1.811	1.852	1.852
CLU 31	0.00902	0.0266	-	-
	0.0493	0.152		
CLU 32	0.0878	0.0603	-0.0482	-0.0482
	0.431	0.259	-0.277	-0.277
CLU 33	0.126	0.107	-0.0641	-0.0641
	0.699	0.614	-0.737	-0.737
CLU 34	0.138	0.131	-0.0264	-0.0264
	0.748	0.713	-0.307	-0.307
CLU 35	0.295	0.289	0.149	0.149
	1.312	1.306	1.387	1.387
CLU 36	0.452	0.459*	-	-
	1.621	1.655		
CLU 37	*	*	-	-
CLU 39	0.203	0.182	-0.00297	-0.00297
	0.878	0.777	-0.0310	-0.0310
CLU 40	0.0659	0.0431	-0.168	-0.168
	0.287	0.172	-1.307	-1.307
CLU 41	0.253	0.264	0.163	0.163
	0.751	0.763	0.514	0.514
CLU 42	0.0147	0.00717	-0.150	-0.150
	0.0670	0.0330	-1.259	-1.259
CLU 43	0.406*	0.384*	0.259**	0.259**
	1.897	1.802	2.480	2.480
CLU 44	0.257	0.236	0.0913	0.0913
	1.187	1.082	0.885	0.885
CLU 45	0.111	-	-	-

	0.708			
CLU 46	0.228	0.219	0.0232	0.0232
	0.999	0.943	0.171	0.171
CONSTANT	-1.234*	-1.271*	-1.218**	-1.308**
	(0.665)	(0.649)	(0.556)	(0.556)
OBSERVATIONS	6,933	6,933	5,980	5,980
NUMBER OF CSO_REF	1,822	1,822	1,692	1,692
AR(1) Z-STATISTIC	-1.783	-1.723	-1.571	-1.637
AR(1) Z-STATISTIC P-VALUE	0.0746	0.0849	0.116	0.102
AR(2) Z-STATISTIC	0.456	0.282	-1.190	-1.123
AR(2) Z-STATISTIC P-VALUE	0.648	0.778	0.234	0.261
HANSEN TEST	20.02	19.51	9.487	9.075
HANSEN TEST P-VALUE	0.171	0.192	0.487	0.525
STANDARD ERRORS IN PARENTHESES *** P<0.01, ** P<0.05, * P<0.1				
ASTERIK CELLS DO NOT MEET THE SDS REQUIREMENT				

Table A.13.1 The effect of the spatial concentration of foreign owned plants within clusters in the North East of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.13.2 The effect of the spatial concentration of foreign owned plants in the North East of England

VARIABLES	FO INTERACTIONS	
INTERMEDIATE INPUTS	0.526***	
	5.617	
EMPLOYMENT	0.514***	
	3.863	
CAPITAL	0.405***	
	2.669	
AGE	-0.578***	
	-2.854	
MULTI SIC	-0.173**	
	-2.237	
MULTI REGION	0.0779	
	1.057	
SINGLE	-0.199**	
	-2.189	
HERFINDAHL	0.619	
	1.299	
CLUSTER INTERACTION	Di FO	Di UK
1 FERROUS METALS AND MANUFACTURING	-0.344	-1.173
	-0.957	-1.130
2 NON-FERROUS METAL MANUFACTURING	-0.0191	0.0238
	-0.576	0.146
3 METAL MANUFACTURING	0.0562	-0.262*
	1.291	-1.716
4 MINERAL EXTRACTION	*	-0.256
	-	-1.467
5 OTHER MINERALS EXTRACTION	*	-0.126
		-0.569
6 MINERAL MANUFACTURING	-0.0289	-0.275***
	-0.451	-2.633
7 BUILDING MATERIALS	-0.0418	-0.285***
	-1.138	-3.099
8 MISCELLANEOUS MANUFACTURING	0.172	-0.234
	1.230	-1.136
9 BREAD AND BISCUITS	-0.0275	-0.207***
	-1.240	-2.651
10 LARGE TRANSPORT MANUFACTURING	*	0.643***

	-	3.979
11 SOAPS AND PERFUMES	-0.127	-0.00822
	-1.175	-0.0138
12 GRAIN AND STARCH	*	-4.372
		-0.958
13 PET FEEDS	*	-0.662
		-1.450
14 LEATHER WORKING	*	1.039
		0.0971
15 PAINTS	0.00746	-0.201
	0.261	-1.473
16 PROCESSING OF FOOD STUFFS	*	-0.0138
		-0.0986
17 EXPLOSIVES AND ORDANCE	*	-0.332***
		-2.796
18 COOKING FATS AND OILS	-	-
19 PROCESSING MEATS	0.0553**	-0.0652
	1.997	-0.571
20 SUGAR	-	-
21 CONFECTIONARY	-0.0128	-0.317
	-0.378	-1.476
22 PAPER PRODUCTS	-0.0206	-0.113
	-0.375	-1.253
23 PRINTING PRODUCTS	0.133**	-0.475**
	2.481	-2.192
24 DISTILLING AND COMPOUNDING	-	-
25 BREWING AND TOBACCO	-0.0195	0.0633
	-1.139	0.475
26 RECREATIONAL MANUFACTURING	-0.0997**	-0.0294
	-2.121	-0.194
27 PRECISION APPARATUS	-0.109**	-0.190
	-2.358	-1.229
28 INORGANIC AND ORGANIC CHEMICALS	-0.0920*	-0.294**
	-1.910	-2.477
29 ESSENTIAL OILS	*	-1.349
		-1.136
30 CHEMICAL AND ADHESIVES	0.503*	-0.625***
	1.738	-2.872

31 MAN MADE FIBRES	*	-2.132
		-1.021
32 RUBBER TYRES	*	-0.167
		-1.614
33 PLASTIC AND RUBBER PRODUCTS	0.213**	-0.273*
	1.990	-1.817
34 ELECTRONIC EQUIPMENT	-0.00758	-0.217
	-0.0780	-1.376
35 WOOD MANUFACTURING	0.0150	-0.0122
	0.343	-0.0974
36 WALL COVERINGS	*	-0.480*
		-1.885
37 SYNTHETIC RUBBER	-	-
38 TRACTORS	-	-
39 VEHICLES	0.0396	-0.350***
	0.636	-2.828
40 TEXTILES	-0.129*	-0.912**
	-1.762	-2.260
41 OTHER TEXTILES	*	-0.126
		-0.637
42 CLOTHING	0.0122	0.253*
	0.702	1.838
43 METAL AND CHEMICAL MACHINERY	0.365*	-0.752**
	1.804	-2.028
44 COMMERCIAL MACHINERY	0.0791**	-0.450**
	2.068	-2.421
45 MINING MACHINERY	-0.144***	-0.237
	-2.891	-1.299
46 OTHER MANUFACTURING	-0.00715	0.509**
	-0.118	2.022
CLU 2	5.944	
	1.083	
CLU 3	5.645	
	1.062	
CLU 4	4.888	
	0.936	
CLU 5	6.797	
	1.205	
CLU 6	4.866	
	0.935	
CLU 7	5.102	

	0.965
CLU 8	5.840 1.033
CLU 9	5.109 0.955
CLU 10	7.295 1.337
CLU 11	4.652 0.767
CLU 12	-27.69 -0.755
CLU 13	2.730 0.547
CLU 14	15.60 0.191
CLU 15	5.670 1.075
CLU 16	5.767 1.050
CLU 17	4.526 0.878
CLU 19	6.196 1.083
CLU 21	4.900 0.940
CLU 22	5.426 1.026
CLU 23	4.800 0.912
CLU 24	147.9 0.923
CLU 25	5.981 1.127
CLU 26	5.557 1.048
CLU 27	5.210 0.967
CLU 28	4.077 0.816
CLU 30	5.484 0.993
CLU 32	5.313 1.028
CLU 33	5.539 1.011
CLU 34	5.116 0.997

CLU 35	6.292
	1.180
CLU 36	5.123
	0.970
CLU 39	4.908
	0.923
CLU 40	1.159
	0.235
CLU 41	6.167
	1.148
CLU 42	7.073
	1.262
CLU 43	4.739
	0.920
CLU 44	4.775
	0.924
CLU 45	4.678
	0.901
CLU 46	8.144
	1.388
1986	-0.0815*
	-1.800
1987	-0.0601
	-1.235
1988	-0.0312
	-0.576
1989	0.0310
	0.579
1990	0.0375
	0.760
1991	-0.189***
	-2.560
1992	-0.113*
	-1.784
1993	-0.0321
	-0.513
1994	-0.0560
	-0.867
1995	0.00894
	0.129
1996	0.161**
	2.274
1997	0.179
	1.349
1998	0.0836
	0.830
1999	-0.212**

	-2.254
2000	-0.267**
	-2.507
2001	-0.218***
	-2.625
2002	-0.130
	-1.605
2003	-0.269
	-1.552
2004	-0.359*
	-1.860
2005	-0.175*
	-1.849
2006	-0.0190
	-0.250
2007	0.219*
	1.941
2008	0.408***
	2.869
2009	0.350***
	2.591
2010	0.540***
	3.800
2011	0.344***
	2.598
2012	0.607***
	3.702
2013	0.613***
	3.833
2014	0.542***
	3.610
CONSTANT	-4.339
	(3.845)
OBSERVATIONS	6,933
NUMBER OF CSO_REF	1,822
AR(1) Z-STATISTIC	-2.286
AR(1) Z-STATISTIC P-VALUE	0.0223
AR(2) Z-STATISTIC	0.679
AR(2) Z-STATISTIC P-VALUE	0.497
HANSEN TEST	29.65
HANSEN TEST P-VALUE	0.197
STANDARD ERRORS IN PARENTHESES	
***** P<0.01, ** P<0.05, * P<0.1**	

Table A.13.3 The effect of the spatial concentration of foreign owned plants in the North East of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.13.3 The effect of the spatial concentration of different ownership types in the North East of England

VARIABLES	EU/ROW/US INT			
INTERMEDIATE INPUTS	0.514***			
	4.833			
EMPLOYMENT	0.551***			
	3.708			
CAPITAL	0.220**			
	2.152			
AGE	-0.424**			
	-2.663			
MULTI SIC	-0.0731*			
	-1.528			
MULTI REGION	0.044			
	0.755			
SINGLE	-0.125**			
	-2.217			
HERFINDAHL	-0.0203			
	-0.081			
CLUSTER INTERACTION	Di UK	Di ROW	Di EU	Di US
1 FERROUS METALS AND MANUFACTURING	0.22	*	0.065	0.0271
	0.373		0.93	0.369
2 NON-FERROUS METAL MANUFACTURING	-0.0605	-0.00144	-0.00797	-0.00487
	-0.462	-0.0986	-0.234	-0.24
3 METAL MANUFACTURING	-0.158	-0.00126	0.0309*	0.0172
	-1.208	-0.0563	1.655	0.97
4 MINERAL EXTRACTION	-	*	-	-
5 OTHER MINERALS EXTRACTION	-14.44	-	*	-
	-0.849			
6 MINERAL MANUFACTURING	-0.189**	*	-0.00221	-0.0331
	-2.183		-0.212	-0.741
7 BUILDING MATERIALS	-0.0874	*	-0.0327	*
	-0.77		-1.05	
8 MISCELLANEOUS MANUFACTURING	-0.372*	0.00426	-0.0171	0.071
	-1.857	0.432	-0.215	1.092

9 BREAD AND BISCUITS	-0.115	*	0.0406**	*
	-1.25		2.426	
10 LARGE TRANSPORT MANUFACTURING	0.439*	*	*	-0.0291
	1.695			-0.595
11 SOAPS AND PERFUMES	-0.563**	*	*	-0.104***
	-2.087			-2.712
12 GRAIN AND STARCH	-	-	-	-
	-	-	-	-
13 PET FEEDS	-	-	*	-
14 LEATHER WORKING	-	-	-	-
15 PAINTS	-0.0877	0.0105	-0.00113	*
	-0.705	0.604	-0.0504	
16 PROCESSING OF FOOD STUFFS	-0.149	*	*	*
	-0.844			
17 EXPLOSIVES AND ORDANCE	1.039*	*	-	*
	1.934			
18 COOKING FATS AND OILS	-	-	-	-
19 PROCESSING MEATS	-0.338**	*	0.0119	*
	-2.036		0.406	
20 SUGAR	-	-	-	-
21 CONFECTIONARY	-0.234*	*	0.00616	*
	-1.653		0.125	
22 PAPER PRODUCTS	-0.094	*	-0.0115	0.000361
	-1.389		-0.648	0.0167
23 PRINTING PRODUCTS	-0.085	*	-0.017	0.022
	-0.816		-1.353	1.256
24 DISTILLING AND COMPOUNDING	-	-	-	-
25 BREWING AND TOBACCO	-0.101	*	*	*
	-0.688			
26 RECREATIONAL MANUFACTURING	0.0159	*	*	0.00625
	0.0986			0.23

27 PRECISION APPARATUS	-0.185	*	-0.0293	-0.00263
	-1.213		-1.334	-0.105
28 INORGANIC AND ORGANIC CHEMICALS	-0.193**	*	0.0191	-0.0531*
	-2.198		0.624	-1.837
29 ESSENTIAL OILS	-	-	-	-
30 CHEMICAL AND ADHESIVES	-0.384***	*	0.0302	0.0269
	-3.137		0.527	0.391
31 MAN MADE FIBRES	-	-	-	-
32 RUBBER TYRES	0.225	*	*	*
	0.0862			
33 PLASTIC AND RUBBER PRODUCTS	-0.223**	0.0301	0.0112	0.183***
	-2.019	1.081	0.217	2.796
34 ELECTRONIC EQUIPMENT	-0.283**	-0.0201	0.00849	0.119
	-2.08	-1.625	0.422	1.574
35 WOOD MANUFACTURING	0.0375	*	0.0533	0.0117
	0.388		1.569	0.9
36 WALL COVERINGS	-	-	-	-
37 SYNTHETIC RUBBER	-	-	-	-
38 TRACTORS	-	-	-	-
39 VEHICLES	-0.149*	0.0279**	0.00199	-0.00038
	-1.94	2.27	0.0726	-0.0121
40 TEXTILES	-0.681**	*	*	*
	-2.286			
41 OTHER TEXTILES	0.181	*	*	*
	1.077			
42 CLOTHING	0.11	0.00641	0.00781	-0.00928
	0.893	0.936	1.114	-0.609
43 METAL AND CHEMICAL MACHINERY	-0.254	-0.0165	0.0595	0.0294
	-1.594	-1.303	1.626	0.427
44 COMMERCIAL MACHINERY	-0.241	*	0.0358	0.0642*
	-1.552		1.511	1.779
45 MINING MACHINERY	-	-	-	-

46 OTHER MANUFACTURING	0.194	0.0860**	-0.0964*	0.144*
	0.934	2.166	-1.836	1.881
CLUSTER DUMMIES				
CLU 1	-			
CLU 2	-1.997			
	-0.632			
CLU 3	-1.711			
	-0.568			
CLU 4	-			
CLU 5	-			
CLU 6	-2.347			
	-0.793			
CLU 7	-1.721			
	-0.574			
CLU 8	-2.811			
	-0.794			
CLU 9	-2.181			
	-0.699			
CLU 10	-0.786			
	-0.232			
CLU 11	-3.989			
	-1.326			
CLU 12	-			
CLU 13	-			
CLU 14	-			
CLU 15	-1.405			
	-0.457			
CLU 16	-2.236			
	-0.742			
CLU 17	-13.74***			
	-2.986			
CLU 19	-3.648			
	-0.994			
CLU 21	-2.518			
	-0.828			
CLU 22	-2.045			
	-0.679			
CLU 23	-1.696			
	-0.564			
CLU 25	-1.602			
	-0.541			

CLU 26	-1.383
	-0.412
CLU 27	-2.231
	-0.696
CLU 28	-2.34
	-0.839
CLU 29	-
CLU 30	-2.723
	-0.902
CLU 33	-1.794
	-0.574
CLU 34	-2.282
	-0.763
CLU 35	-0.761
	-0.259
CLU 36	-
CLU 37	-
CLU 38	-
CLU 39	-2.036
	-0.705
CLU 40	-5.337*
	-1.735
CLU 41	0.188
	0.0514
CLU 42	-1.146
	-0.369
CLU 43	-2.042
	-0.656
CLU 44	-1.801
	-0.614
CLU 45	-
CLU 46	0.147
	0.0455
YEAR	
1986	-0.0824*
	-1.937
1987	-0.0519
	-1.146
1988	-0.0162
	-0.242
1989	-0.056
	-0.898

1990	-0.0461
	-0.784
1991	-0.113*
	-1.831
1992	-0.103
	-1.588
1993	-0.0832
	-1.205
1994	-0.0822
	-1.121
1995	0.0211
	0.171
1996	0.123
	1.575
1997	0.220**
	2.2
1998	0.0132
	0.12
1999	-0.177*
	-1.801
2000	-0.209**
	-1.986
2001	-0.137
	-1.381
2002	-0.0969
	-0.846
2003	-0.0863
	-0.928
2004	-0.202*
	-1.729
2005	-0.0225
	-0.228
2006	0.0128
	0.0947
2007	0.268**
	2.054
2008	0.316**
	2.249
2009	0.258**
	2.5
2010	0.309**
	2.443
2011	0.237**
	1.988
2012	0.343***
	2.896
2013	0.475***

	4.038
2014	0.482**
	2.42
CONSTANT	1.848
	-3.479
OBSERVATIONS	5,980
NUMBER OF CSO_REF	1,692
AR(1) Z-STATISTIC	-1.303
AR(1) Z-STATISTIC P-VALUE	0.193
AR(2) Z-STATISTIC	-1.542
AR(2) Z-STATISTIC P-VALUE	0.123
HANSEN TEST	9.61
HANSEN TEST P-VALUE	0.962

Table A.13.3 The effect of the spatial concentration of different ownership types in the North East of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.13.4 The effect of the spatial concentration of foreign owned plants within clusters in the North and South East of England

VARIABLES	NORTH FO	NORTH EU/ROW/US	SE FO	SE EU/ROW/US
INTERMEDIATE INPUTS	0.729***	0.544***	0.521***	0.514***
	7.419	3.731	4.401	3.352
EMPLOYMENT	0.230*	0.346**	0.396***	0.463***
	1.906	2.167	3.547	3.023
CAPITAL	0.361*	0.301**	0.128*	0.196*
	1.867	2.333	1.772	1.794
DI FO	0.00714	-	-0.139**	
	1.472		-2.339	
DI UK	-0.0835**	-0.0529**	0.184*	0.0858
	-2.168	-2.249	1.852	0.820
DI ROW	-	0.00383**		-0.00935*
		2.182		-1.178
DI US	-	0.00514*		-0.0240
		1.999		-1.333
DI EU	-	0.00268		-0.0502
		0.679		-1.473
AGE	-0.647**	-0.513***	-0.203**	-0.335**
	-2.188	-2.869	-2.151	-2.076
MULTI SIC	-0.0972	-0.0453	0.00232	-0.0491
	-1.362	-1.113	0.0907	-1.340
MULTI REGION	-0.0600	0.0152	0.0794**	0.0591
	-1.151	0.329	2.313	1.418
SINGLE	-0.0814*	-0.0539	0.0106	-0.00244
	-1.699	-1.402	0.404	-0.0728
HERFINDAHL	-0.249	0.00253	-0.0625	-0.0652
	-1.505	0.0202	-0.612	-0.656
1986	-0.0269	0.0175	-0.0242	-0.0353
	-0.944	0.908	-1.251	-1.328
1987	-0.0191	0.0483	-0.0419**	-0.0112
	-0.605	2.060	-2.099	-0.343
1988	-0.0301	0.0485**	0.0313	0.0170
	-0.811	1.975	1.029	0.557
1989	-0.0297	0.0593*	0.0144	0.0247
	-0.623	1.727	0.586	0.663
1990	-0.00570	0.0793**	0.0270	0.0339
	-0.138	2.086	0.798	0.676
1991	-0.0780	0.0446	-0.0220	0.0210
	-1.412	1.118	-0.683	0.410
1992	-0.0386	0.0362	-0.0439	-0.00989
	-0.914	0.785	-1.302	-0.180
1993	-0.139*	0.0239	-0.00963	0.0423

	-1.861	0.451	-0.244	0.639
1994	-0.134	0.0513	0.0926*	0.109
	-1.424	0.901	1.771	1.431
1995	-0.0415	0.0944	0.0290	0.0890
	-0.601	1.586	0.624	1.290
1996	0.0181	0.117**	0.127***	0.197***
	0.342	2.192	2.632	2.549
1997	-0.0139	0.0752	0.0973	0.195*
	-0.191	0.864	1.351	1.806
1998	-0.0835	0.0470	0.0621	0.137
	-1.123	0.721	1.025	1.311
1999	-0.219	-0.0308	0.000709	-0.00268
	-1.767	-0.360	0.0111	-0.0266
2000	-0.223*	-0.0144	0.0676	0.0871
	-2.100	-0.215	0.923	0.760
2001	-0.206*	-0.0191	0.0718	0.0615
	-1.905	-0.259	0.915	0.523
2002	-0.208	0.00862	0.301*	0.195
	-1.609	0.0947	1.875	1.169
2003	-0.199*	-0.0210	0.0915	0.0769
	-1.765	-0.225	1.045	0.584
2004	-0.249*	-0.197**	0.0155	-0.0209
	-1.867	-2.351	0.189	-0.168
2005	-0.103	0.0779	0.128	0.129
	-1.417	1.056	1.484	1.040
2006	-0.0787	0.0929	0.180*	0.204
	-0.821	1.069	1.955	1.534
2007	0.183*	0.281**	0.169*	0.303**
	1.954	2.126	1.718	2.196
2008	0.132*	0.229**	0.144*	0.314***
	1.763	2.004	1.640	2.576
2009	0.283***	0.433***	0.362***	0.476***
	3.034	4.569	4.535	4.170
2010	0.340***	0.303***	0.239***	0.302***
	2.881	2.813	2.982	3.032
2011	0.235***	0.259***	0.152	0.313***
	3.204	2.811	1.619	3.696
2012	0.268***	0.250***	0.443***	0.707***
	3.374	3.145	3.945	4.095
2013	0.214***	0.257**	0.279*	0.605***
	2.888	2.543	1.928	4.139
2014	0.257***	0.282***	0.361***	0.575***
	2.757	2.651	3.421	3.576
CLU 1				
CLU 2	0.158*	0.0748	-1.264*	-0.394
	1.679	1.013	-1.866	-0.626

CLU 3	0.335**	0.227***	-1.210*	-0.301
	2.326	2.547	-1.811	-0.504
CLU 4	0.195	0.0166	-1.970**	-1.005
	1.559	0.140	-2.168	-1.082
CLU 5	-0.282	0.855***	-44.38**	
	-1.128	3.241	-2.312	
CLU 6	0.116	0.0839	-1.170*	-0.214
	1.374	1.135	-1.722	-0.359
CLU 7	0.306**	0.267	-1.053	-0.179
	2.143	1.530	-1.562	-0.259
CLU 8	0.0515	0.0694	-1.238*	-0.368
	0.761	1.139	-1.901	-0.628
CLU 9	0.361	-0.0237	-1.842**	-1.078
	1.157	-0.118	-2.226	-1.237
CLU 10	-0.119	-0.0977	-1.753*	-0.439
	-0.447	-0.388	-1.890	-0.638
CLU 11	-0.192	-0.0450	-1.435**	-0.563
	-1.071	-0.380	-2.048	-0.873
CLU 12	0.00957	-	-1.086	
	0.0467		-1.415	
CLU 13	0.00183	0.211	-1.231	-0.331
	0.0128	1.072	-1.563	-0.474
CLU 14	0.271	-	-1.903**	
	1.448		-2.146	
CLU 15	0.234**	0.235**	-1.337*	-0.421
	2.172	2.475	-1.938	-0.671
CLU 16	-0.165	-0.0237	-1.582**	-0.913
	-1.436	-0.288	-2.182	-1.223
CLU 17	-0.0240	0.184	-1.204	-0.0163
	-0.131	0.858	-1.602	-0.0243
CLU 18	-	-	-2.103*	-
			-1.922	
CLU 19	-0.118	-0.0324	-1.625**	-0.753
	-1.232	-0.305	-2.169	-1.097
CLU 20	-	-	-	-
CLU 21	0.195	0.0193	-1.308**	-0.622
	1.571	0.210	-1.981	-0.994
CLU 22	-0.0113	0.0289	-1.273**	-0.488
	-0.136	0.459	-2.016	-0.841
CLU 23	0.455***	0.215**	-1.248*	-0.260
	2.767	1.810	-1.805	-0.402
CLU 24	-0.437	0.120	-127.8**	
	-1.284	0.417	-2.017	
CLU 25	-0.0495	0.202	-1.173*	-0.292
	-0.217	1.156	-1.675	-0.454
CLU 26	0.317**	0.160*	-1.253*	-0.344

	2.145	1.752	-1.827	-0.545
CLU 27	0.416**	0.271***	-1.295*	-0.459
	2.415	2.757	-1.864	-0.688
CLU 28	-0.414	-0.168	-1.528**	-0.670
	-1.499	-1.051	-2.042	-0.988
CLU 29	0.217	0.365*	-1.472**	-22.41
	1.488	1.846	-1.793	-0.0666
CLU 30	0.0200	0.108	-1.122**	-0.391
	0.113	0.815	-1.809	-0.654
CLU 31	-0.131	-	-0.131	
	-0.657		-0.657	
CLU 32	0.156	0.0399	-1.646**	-0.514
	0.837	0.245	-2.039	-0.698
CLU 33	0.0922	0.0552	-1.357**	-0.481
	1.183	1	-2.017	-0.804
CLU 34	0.104	0.0799	-1.335**	-0.449
	1.210	1.218	-2.030	-0.758
CLU 35	0.152	0.151*	-1.394**	-0.515
	1.345	1.720	-1.959	-0.787
CLU 36	-0.0904	-	-2.449**	
	-0.624		-2.159	
CLU 37	-0.387	-	-1.838*	
	-1.350		-1.869	
CLU 38	0.501*	-	-1.750**	
	1.763		-2.016	
CLU 39	0.174	0.155	-1.298*	-0.415
	1.307	1.452	-1.956	-0.717
CLU 40	0.0935	0.0339	-1.561**	-0.444
	1.071	0.548	-2.040	-0.675
CLU 41	0.454	0.486*	-1.195*	-0.625
	1.469	1.783	-1.785	-1.028
CLU 42	0.313	0.159	-1.300*	-0.289
	1.313	0.979	-1.868	-0.500
CLU 43	0.353**	0.276***	-1.255*	-0.307
	2.394	3.135	-1.851	-0.517
CLU 44	0.301*	0.191**	-1.270*	-0.431
	1.946	2.124	-1.824	-0.671
CLU 45	0.361	-	-2.090**	
	1.429		-2.220	
CLU 46	0.101	0.0881	-1.321**	-0.415
	1.244	1.329	-1.924	-0.663
CONSTANT	1.790	0.596	1.310	0.273
	(1.351)	(0.751)	(0.950)	(1.019)
OBSERVATIONS	35,727	31,257	17,061	15,317
NUMBER OF CSO_REF	9,070	8,542	4,890	4,660
AR(1) Z-STATISTIC	-1.200	-2.143	-4.465	-3.797

AR(1) Z-STATISTIC P-VALUE	0.230	0.0321	7.99e-06	0.000147
AR(2) Z-STATISTIC	-1.128	0.0325	-0.767	-0.0986
AR(2) Z-STATISTIC P-VALUE	0.259	0.974	0.443	0.921
HANSEN TEST	5.241	1.899	36.65	32.41
HANSEN TEST P-VALUE	0.155	0.965	0.102	0.147
STANDARD ERRORS IN PARENTHESES				
***** P<0.01, ** P<0.05, * P<0.1**				

Table A.13.4 The effect of the spatial concentration of foreign owned plants within clusters in the North and South East of England

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.14 Underlying figures for the effect of spatial concentration over time

A.14.1 Di values for FO and UK owned plants in the North East of England over time

VARIABLES	FO EFFECT	
INTERMEDIATE INPUTS	0.513***	
	6.512	
EMPLOYMENT	0.359***	
	3.682	
CAPITAL	0.305***	
	2.822	
AGE	-0.440***	
	-2.834	
MULTI SIC	-0.0932*	
	-1.816	
MULTI REGION	0.120**	
	2.465	
SINGLE	-0.0524	
	-1.335	
HERFINDAHL	0.153	
	1.481	
	UK Owned	**FO Owned**
1986	-0.180***	-0.0281***
	-2.903	-3.743
1987	-0.116**	-0.0197**
	-1.967	-2.207
1988	0.0549	0.0243
	1.135	1.408
1989	0.0277	0.0152
	0.818	1.306
1990	-0.0298	-0.00588
	-0.716	-0.440
1991	-0.0394	0.0107
	-0.924	0.677
1992	0.000234	0.0183
	0.00633	0.911
1993	-0.203**	-0.0108
	-2.512	-0.608
1994	-0.222**	-0.0423***
	-2.215	-2.626
1995	-0.0951	-0.00830
	-1.621	-0.814
1996	-0.102*	-0.0180
	-1.916	-1.397

1997	-0.0339	0.00776
	-0.553	0.785
1998	0.146**	-0.00406
	2.026	-0.356
1999	-0.0490	-0.0154
	-0.544	-1.602
2000	-0.257**	-0.0117*
	-2.126	-1.826
2001	-0.134*	0.00365
	-1.929	0.178
2002	0.0532	0.0347
	0.473	0.974
2003	0.0311	0.0342
	0.113	1.053
2004	-0.246	0.0163
	-1.344	0.541
2005	-0.376***	-0.00676
	-3.591	-0.452
2006	-0.126	0.00142
	-1.333	0.0722
2007	-0.129	0.0214
	-0.937	0.839
2008	0.0201	-0.00168
	0.0925	-0.0548
2009	-0.335	-0.0342
	-0.998	-0.720
2010	0.241	-0.00968
	0.886	-0.230
2011	-0.0190	-0.0726
	-0.0701	-1.237
2012	0.831**	0.122**
	2.509	2.329
2013	-0.487*	0.0402
	-1.813	1.222
2014	-0.175	0.0663***
	-0.745	2.768
1986	-0.765***	
	-3.097	
1987	-0.432	
	-1.581	
1988	0.51	
	1.523	
1989	0.374	
	1.646	
1990	0.0195	
	0.0929	
1991	-0.0223	

	-0.0965
1992	0.199
	0.955
1993	-0.756**
	-2.409
1994	-0.99**
	-2.393
1995	-0.242
	-1.023
1996	-0.223
	-0.782
1997	0.207
	0.547
1998	0.809**
	2.074
1999	-0.144
	-0.298
2000	-1.034**
	-2.233
2001	-0.43
	-1.154
2002	0.522
	0.856
2003	0.373
	0.332
2004	-0.795
	-0.931
2005	-1.487***
	-3.078
2006	-0.307
	-0.804
2007	-0.188
	-0.328
2008	0.458
	0.464
2009	-1.157
	-0.728
2010	1.431
	1.055
2011	-0.0392
	-0.0291
2012	4.517***
	2.698
2013	-1.396
	-1.115
2014	0.0584
	0.0617

CLU 2	-0.0356
	-0.458
CLU 3	0.293***
	2.630
CLU 4	0.0807
	0.560
CLU 5	-0.373**
	-2.342
CLU 6	0.0319
	0.348
CLU 7	0.239
	1.569
CLU 8	0.0566
	0.693
CLU 9	-0.0826
	-0.650
CLU 10	0.0557
	0.282
CLU 11	-0.129
	-0.583
CLU 12	0.369
	1.280
CLU 13	0.232
	1.398
CLU 14	0.202
	1.037
CLU 15	0.219**
	2.118
CLU 16	-0.110
	-1.179
CLU 17	0.206
	0.995
CLU 19	-0.0362
	-0.311
CLU 21	0.0538
	0.558
CLU 22	-0.00323
	-0.0428
CLU 23	0.115
	1.150
CLU 24	15.06
	0.691
CLU 25	0.147
	1.085
CLU 26	0.127
	1.339
CLU 27	0.366**

	2.410
CLU 28	-0.217
	-1.513
CLU 29	0.0299
	0.203
CLU 30	0.0631
	0.456
CLU 31	-0.0400
	-0.438
CLU 32	-0.125
	-1.122
CLU 33	-0.00285
	-0.0397
CLU 34	0.0465
	0.647
CLU 35	0.143
	1.407
CLU 36	0.155
	1.121
CLU 37	*
CLU 39	0.0804
	0.836
CLU 40	0.00979
	0.0937
CLU 41	0.224
	1.117
CLU 42	0.0123
	0.111
CLU 43	0.317***
	2.920
CLU 44	0.101
	1.078
CLU 45	0.0122
	0.148
CLU 46	0.113
	1.050
CONSTANT	0.397
	(0.769)
OBSERVATIONS	6,933
NUMBER OF CSO_REF	1,822
AR(1) Z-STATISTIC	-1.994
AR(1) Z-STATISTIC P-VALUE	0.0462
AR(2) Z-STATISTIC	-0.678

AR(2) Z-STATISTIC P-VALUE	0.498
HANSEN TEST	18.73
HANSEN TEST P-VALUE	0.226
STANDARD ERRORS IN PARENTHESES	
***** P<0.01, ** P<0.05, * P<0.1**	

Table A.14.1 Di values for FO and UK owned plants in the North East of England over time

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.14.2 Di values for EU, ROW, US and UK owned plants in the North East of England over time

VARIABLES	EU/ROW/US EFFECT			
INTERMEDIATE INPUTS	0.572***			
	5.555			
EMPLOYMENT	0.489***			
	2.901			
CAPITAL	0.0364			
	0.318			
AGE	-0.121			
	-0.821			
MULTI SIC	-0.0183			
	-0.372			
MULTI REGION	0.0800*			
	1.747			
SINGLE	-0.0284			
	-0.550			
HERFINDAHL	0.167			
	1.139			
	UK Owned	**EU Owned**	**ROW Owned**	**US Owned**
1986	-0.0341	-0.0162**	-0.00270	-0.00491
	-0.389	-2.431	-0.348	-0.441
1987	0.0212	0.00303	*	0.00519
	0.219	0.135	*	0.814
1988	-0.161	-0.0120	-0.0377	0.014
	-0.434	-0.809	-0.608	1.592
1989	0.0368	0.00443	0.00268	0.0136
	0.828	0.463	0.186	1.563
1990	-0.00407	0.00332	-0.0188	0.00726
	-0.0930	0.353	-1.318	0.679
1991	0.0261	-0.00628	-0.00614	0.00654
	0.410	-0.640	-0.339	0.423
1992	0.0629	-0.00535	-0.00556	0.00924
	1.082	-0.782	-0.389	0.627
1993	0.0246	-0.00490	-0.00150	0.0154
	0.127	-0.343	-0.139	0.564
1994	-0.0556	-0.0109	-0.0160	-0.0142
	-0.271	-0.740	-0.426	-0.760
1995	0.0159	-0.00923	0.000398	0.00224
	0.200	-0.932	0.0338	0.182
1996	-0.0872	-0.0156	-0.0127	0.00684
	-1.246	-1.527	-1.124	0.579
1997	-0.154	-0.00770	-0.0131	0.0254
	-0.995	-0.802	-1.399	1.042
1998	0.216	0.0557*	0.0511*	0.0297

	1.618	1.749	1.818	0.927
1999	-0.329	-0.00286	-0.0497**	0.00838
	-1.608	-0.215	-2.090	0.526
2000	0.00197	-0.00731	-0.00465	0.0041
	0.0144	-1.463	-0.662	0.342
2001	-0.0585	0.0163	-0.00379	-0.0125
	-0.431	0.822	-0.835	-0.787
2002	0.228	0.0467	0.00724	-0.0069
	1.227	1.384	0.597	-0.480
2003	0.270	0.0177	-0.00261	0.00306
	0.854	0.775	-0.257	0.0804
2004	-0.192	0.00497	-0.00593	-0.0232
	-1.007	0.192	-0.536	-1.355
2005	-0.256	-0.00195	0.00346	-0.0259
	-1.319	-0.326	0.375	-1.907
2006	0.0284	-0.00525	0.0108	-0.0151
	0.246	-0.617	0.960	-1.452
2007	-0.119	-0.0208	0.0107	0.0108
	-0.633	-0.881	0.741	0.309
2008	-0.0784	-0.105*	0.0476*	0.00769
	-0.228	-1.686	1.836	0.485
2009	-0.249	0.0628	-0.0697	0.0129
	-0.584	0.909	-1.975	0.562
2010	0.0650	-0.0266	0.0254	0.000707
	0.163	-0.703	0.891	0.0218
2011	0.154	-0.00868	0.0480	-0.0488
	0.534	-0.384	2.544	-1.528
2012	0.806	0.00837	0.0277	0.089
	1.004	0.207	0.783	0.916
2013	-0.283	-0.0292	-0.0343	0.0523***
	-0.466	-1.082	-0.366	2.697
2014	-0.147	0.00925	-0.00605	0.021
	-0.439	0.315	-0.375	1.621
CLU 2	0.0245			
	0.292			
CLU 3	0.130*			
	1.736			
CLU 5	-0.0517			
	-0.229			
CLU 6	0.165			
	1.335			
CLU 7	0.424*			
	1.837			
CLU 8	-0.0101			
	-0.157			
CLU 9	-0.364**			
	-2.456			

CLU 10	-0.758**
	-2.153
CLU 11	-0.0431
	-0.170
CLU 13	0.563**
	2.302
CLU 15	0.172
	1.244
CLU 16	-0.131
	-0.950
CLU 17	0.341
	0.845
CLU 19	-0.267
	-2.987
CLU 21	0.0470
	0.431
CLU 22	0.0830
	0.873
CLU 23	0.182*
	1.756
CLU 25	0.427*
	1.897
CLU 26	0.0855
	0.948
CLU 27	0.240*
	1.754
CLU 28	0.0605
	0.333
CLU 29	0.00599
	0.0197
CLU 30	0.352
	1.470
CLU 32	0.170
	0.893
CLU 33	0.0284
	0.379
CLU 34	0.0131
	0.224
CLU 35	0.0570
	0.707
CLU 39	0.0348
	0.467
CLU 40	-0.0549
	-0.572
CLU 41	-0.0690
	-0.263
CLU 42	-0.138

	-1.389
CLU 43	0.216**
	2.558
CLU 44	0.0706
	0.838
CLU 46	0.0244
	0.293
1986	-0.5
	-1.06
1987	0.011
	0.02
1988	-1.188
	-0.51
1989	0.122
	0.38
1990	-0.277
	-0.78
1991	-0.158
	-0.29
1992	-0.004
	-0.01
1993	-0.103
	-0.1
1994	-0.697
	-0.62
1995	-0.078
	-0.19
1996	-0.564
	-1.02
1997	-0.819
	-0.94
1998	1.732
	1.81
1999	-1.931
	-1.65
2000	-0.261
	-0.41
2001	-0.468
	-0.69
2002	0.998
	1.02
2003	0.959
	0.6
2004	-1.126
	-1.17
2005	-1.362
	-1.46

2006	-0.009
	-0.01
2007	-0.561
	-0.59
2008	-0.571
	-0.31
2009	-1.055
	-0.55
2010	0.383
	0.21
2011	0.638
	0.45
2012	4.154
	1.08
2013	-1.117
	-0.37
2014	-0.381
	-0.27
CONSTANT	-0.959
	(0.847)
OBSERVATIONS	5,980
NUMBER OF CSO_REF	1,692
AR(1) Z-STATISTIC	-2.158
AR(1) Z-STATISTIC P-VALUE	0.0309
AR(2) Z-STATISTIC	-0.579
AR(2) Z-STATISTIC P-VALUE	0.563
HANSEN TEST	5.568
HANSEN TEST P-VALUE	0.850
STANDARD ERRORS IN PARENTHESES	
***** P<0.01, ** P<0.05, * P<0.1**	

Table A.14.2 Di values for EU, ROW, US and UK owned plants in the North East of England over time

The asterisk cell indicates the values where the number of enterprises does not reach the required SDS threshold of more than ten enterprises for release.

A.14.3 Di values for EU, ROW, US and UK owned plants in the North East of England over time

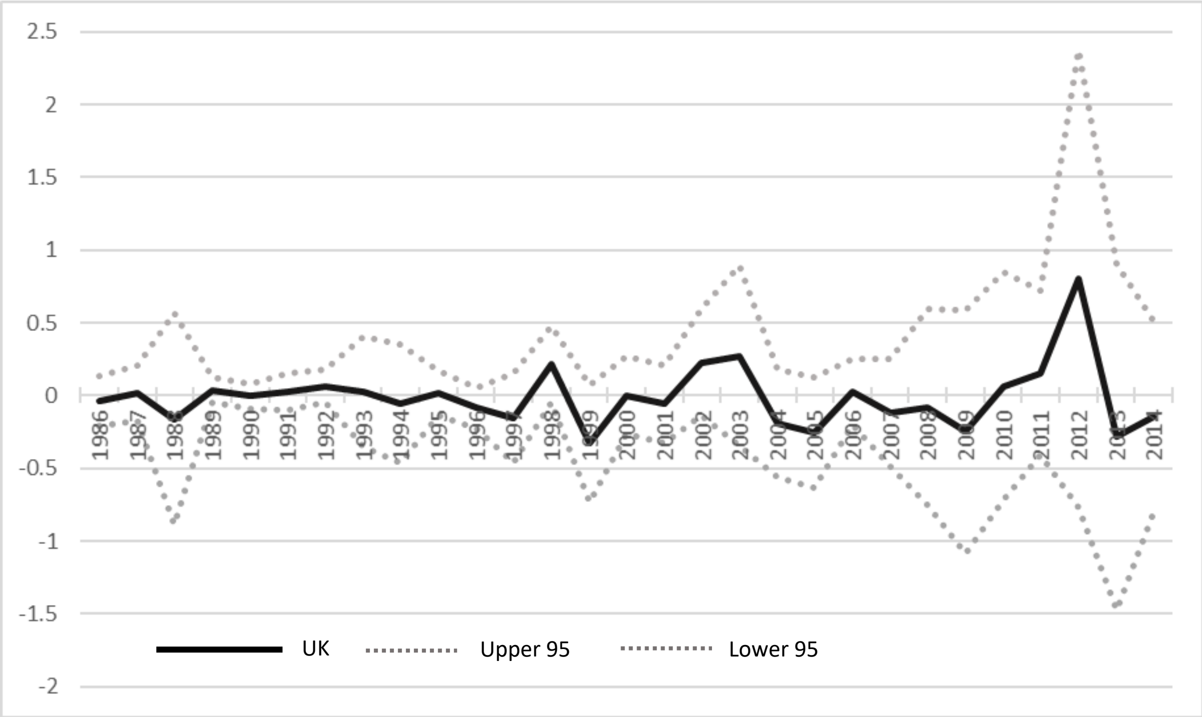

Figure A.14.1 The Effect of the spatial concentration of other UK owned plants to UK owned plants in the North East of England

Figure A.14.1 plots the influence of the presence of other UK owned plants on the productivity of UK owned plants within clusters for the regression with the different ownership groups. There are no periods where the presence of other UK owned plants has a significant impact, positive or negative, on productivity in UK owned plants.